Essays in Macro and Labor Economics

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BY

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Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work.

Chapter 3 of this thesis is co-authored with Balazs Stadler from the Organization of Economic Cooperation and Development.

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Jan-Luca Hennig

Non-Technical Summary

This dissertation consists of three essays at the intersection of labor economics and macroeconomics. It tackles macroeconomic questions with a focus on labor markets. It makes use of micro level and regional level data in order to understand how macroeconomic developments affect labor market outcomes of individuals.

Chapter 2 combines two intensively discussed topics at the intersection of labor economics and macroeconomics, namely labor market polarization and intergenerational mobility. This paper investigates whether there is a causal relationship between rising labor market polarization and declining intergenerational mobility in the United States. The former relates to the disappearance of middle-wage routine jobs and the rise of both high- and low-income jobs. The latter measures the cross-generational link between the income of parents and that of their children. The rising demand for extreme skills in the labor market - driven by falling costs for information and communications technology - induces young generations to attain either very high or very low levels of education. Children from low-income parents typically experience less parental support, in particular to finance high educational attainment. This lower level of parental investment into children's education implies limited chances for upward economic mobility for children from low-income parents. On the other hand, children of high-income parents have better access to high levels of education, and are therefore less likely to fall down the economic ladder. Therefore, children from both low- and high-income parents are less likely to make cross-generational transitions in terms of employment, occupational group and income. Children of middle-income parents are also more likely to choose very high or very low levels of educational attainment, consequently parental income becomes less important for the children's incomes.

Chapter 3 examines the development and the role of firms in the gender pay gap in 21 European countries. It exploits information on employees and employers to understand how firms contribute to the gender wage gap. Firms can contribute to the earnings inequality between men and women in two ways. First, women receive lower wages than men from the same firm. Second, men and women can work for employers with differing in the wages they pay their employees. The paper shows that both factors on average play an equivalent role, but it finds strong heterogeneity across countries. The gender wage gap also grows with age, and the analysis provides evidence that women and men increasingly work in different firms in terms of wage payments. The rising divergence of employer segregation between men and women can be associated with family formation. The paper relates distinct institutional settings to the two factors of how firms contribute to the gender pay gap. A higher incidence of central wage bargaining in a firm tends to increase the gender wage gap, which is possibly driven by bonuses. Family policies which allow a better work-life balance for women tend to reduce the wage gap caused by sorting into different firms, in particular for age groups after family formation.

Chapter 4 explores the interaction between trade shocks and labor market frictions for eight Western European countries. The rise of China in global commodity markets since the beginning of this century has adversely affected many manufacturing workers in advanced economies. Previous research typically focused on regional variation within a country, and these studies typically find heterogeneous average responses in the magnitude of the decline in manufacturing employment. One potential explanatory factor behind these may be labor market institutional settings because they impact employment decisions of both workers and firms. The paper investigates whether labor market frictions exacerbate the detrimental impact of the rise in import competition from China on manufacturing employment, and which sector of activity absorbs this adverse shock. The main finding confirms that regions more exposed to the rise of China have suffered from a reduction in manufacturing employment shares, and that this shock grows larger with regional labor market friction. Moreover, the paper finds that employment in public services, and not in construction or private services sector, absorbed the negative shock to the manufacturing sector. The unemployment rate, the labor force participation rate, and wages in all sectors are largely unresponsive to import competition from China.

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[1] Yes, this is a 2Pac reference.

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Chapter 1

General Introduction

This dissertation is a collection of three essays at the intersection of labor economics and macroeconomics. While the research topics are diverse within the area of labor economics, some common elements exist. All chapters evaluate how labor market outcomes change due to developments outside of workers' direct control, e.g. automation in Chapter 2 on educational choice, changes in firm pay-differentials in Chapter 3 on the gender wage gap, and the rise of China in global commodity markets on employment and wages in Chapter 4. The main link between Chapters 3 and 4 is the investigation of institutional settings and how they are linked to labor market outcomes of workers. All chapters are of empirical nature, and Chapter 2 also develops a theoretical framework. Specifically, they all exploit microeconomic data on either workers, regions, firms, or a combination thereof. Chapters 2 and 4 work with worker and regional data, while Chapter 3 combines data on workers and employers.

The first essay (Chapter 2) presents theoretical and empirical that the rise of automation technologies, and the subsequent polarization of the labor market, does not only have a detrimental impact on contemporaneous workers in vulnerable occupations in terms of employment and wages, but also on future generations in terms of educational attainment, intergenerational elasticity and upward mobility.

The "American Dream" allows everyone to be successful regardless of their geographic and family background. However, the United States has turned into one of the least socially mobile countries among advanced economies, and with stark differences within the United States. At the same time, labor market polarization affects different parts of the income distribution, in particular middle-income routine occupations. The paper exploits variation over time and across space to investigate how labor market polarization influences children in their educational choice, which translates into intergenerational mobility.

The study first develops an overlapping-generations model with spatial heterogeneity and three different occupational groups based on the task framework. It focuses on educational choices and cross-generational transitions across educational and occupational groups, which has direct consequences on children's incomes. The model delivers testable predictions on educational choice and intergenerational elasticity for children from all parental backgrounds, and on upward mobility for children from low-income parents.

The paper confronts the model predictions with empirical evidence exploiting data from Decennial Censuses and the Panel Study of Income Dynamics (PSID). The paper firstly shows that during the last decades education of young labor force entrants has polarized, with a simultaneous increase in average educational attainment. The strongest rise in educational polarization occurred during the 1990s, which aligns with the timing of the IT revolution. This finding is confirmed when calculating family premia and educational polarization indices for various education levels dependent on parental background. The paper also finds evidence that stronger labor market polarization leads to more polar educational choices across time and space.

The model predicts stronger intergenerational elasticity for children whose parents work in either high- or low-skill occupations because cross-generational transitions out of high and low education groups, and thus occupation and income, are less likely. By implication, the incomes of children of workers in such occupations depend greatly on parental incomes. On the other hand, for children with parents in routine occupations, which are negatively affected by the rise of IT, intergenerational elasticity is lower as they increasingly choose either low or high educational attainment levels. Empirical evidence confirms these predictions and it shows that the pattern goes hand in hand with progressing labor market polarization.

Another prediction of the model relates to upward mobility for children from low-income parents. As cross-generational transitions out of manual occupations are less likely with a falling price for information and communication technology capital, labor market polarization impedes social mobility for children whose parents work in these occupations. Precisely, a one percentage point increase in labor market polarization measured by the decrease in routine employment shares reduces the expected rank of children from low-income parents by .57.

These findings are important as they highlight impact of labor market polarization with educational choice as a key channel on intergenerational mobility. They show that parents involuntarily pass the detrimental impact of labor market polarization on their children by limiting the set of educational choices they can make. These results also speak to the ongoing technological advancement such as robotics and artificial intelligence. They show that in order to allow children from all backgrounds to achieve their potential in the future, it is crucial to identify vulnerable occupations and insure the opportunity of high educational attainment of the children of such workers.

The second essay (Chapter 3) demonstrates how firms' contribute to the gender wage gap and decomposes the firm pay-differentials into a within-firm component and a between-firm component, which are of equal importance. The latter drives the rising gender wage gap over the life cycle, and policymakers can address it with multiple family policies, which focus on encouraging and enabling women to return fast to the labor market after maternity leave.

The decline in gender gaps with respect to education, employment and wages have shrunk is one of the strongest trends in the second half of the 20$^{\text{th}}$ century. Yet, in the last two decades the gender pay gap only shrank slowly despite a substantial gap of around 14 percent between men and women with similar observable characteristics in Europe. At the same time, firms – in the form of pay premia – have been associated with rising overall wage inequality. The paper therefore concentrates on how firm pay-differentials affect the pay gap between men and women.

The first step is to estimate the overall contribution of firm pay premia to the gender wage gap. Similar to the previous literature, the paper focuses on the lower-bound estimate and find that pay premia contribute at least 36 percent to the gender wage gap in 2014. However, the paper uncovers strong heterogeneity across countries, ranging from 11 percent for France up to 77 percent for Hungary.

Next, the study decomposes the firms' contribution into a within-firm and a between-firm component. Both components are equally important in 2014, before the within-component played a slightly larger role. Overall, the decline in the gender pay gap between 2002 and 2014 is largely driven by the former, while the latter is largely unchanged over time.

The paper then examines the role of both components for various demographic groups, differentiating by education and age. The within-firm component declines the strongest within the group of employees with primary education and less for the group with secondary and tertiary education. The decline in the within-firm component for the group of employees with tertiary education is completely offset by a rise in the between-firm component. This finding is consistent with previous findings of glass ceilings in Europe, but instead of not having access to high-paying positions within firms, high-skilled women tend to not work for high-paying firms.

The analysis of both components by age group shows that, on average in Europe, the within-firm component matters more than the between-firm component for female labor market entrants. This result is indicative of discrimination towards women, potentially based on future fertility concerns, at an early career stage. However, the between-firm component increases over the life cycle, and is more important after the age of 40. The paper shows that the well-known pattern of rising gender pay gaps across the life cycle is driven by the between-firm component. On the other hand, the within-firm component stays largely constant across the life cycle.

The last step of the paper is to investigate how institutional settings relate to each component. Specifically, the study relates the within-firm component to firm-level differences in the incidence of collective bargaining, and the between-firm component to family policies. The results suggest that less centralized bargaining is associated with smaller gender wage gaps. One potential explanation is that under central bargaining regimes, actual wages differ stronger from negotiated wages, where the former includes bonus payments, and from which men benefit more often than women.

Finally, the paper considers eight family policy indicators and their relationship with the between-firm component for all age groups and by age category. The paper conducts the analysis by age group as the between-firm component is rising substantially over the life cycle. Extending childcare enrolment of young children and reducing the length of maternity leave benefits reduces the between-firm component of the gender pay gap for age groups after family formation, but not before. The impact peters out over the life cycle, but the findings indicate that they have a long-lasting impact.

The findings in this study are meaningful for various reasons. First, they show that firm pay premia form a substantial share of the gender pay gap. Second, they contribute to the rise over the life cycle though the between-firm component. This implies that women tend to work in low-paying firms after family formation. Third, carefully designed family policies have the potential to reduce the between-firm component and help to reduce the gender wage gap in the future.

The third essay (Chapter 4) shows that the rise of import competition from China adversely affects manufacturing workers in Europe in terms of employment, and labor market frictions exacerbate this detrimental outcome. At the same time, the public sector tends to absorb the negative impact.

There has already been a debate in the 1990s as to whether trade with low-income countries has any repercussions on workers' wages in advanced economies. However, the debate ended prematurely and inconclusive, partly because imports from low-income countries were small. The rise of China in global commodity markets, in particular in combinations with its entry into the WTO in 2001, and its consequences on manufacturing workers in the United States has been subject to recent public and academic debate. However, the percentage change of Chinese imports in Europe has risen more compared to the United States between 2002 and 2006.

Previous studies focusing on either the United States or single European countries typically find a detrimental impact of Chinese import competition on manufacturing employment in more exposed regions. However, the actual impact varies substantially despite the same estimation strategy. One potential explanation for the heterogeneous findings are differences in labor market institutional settings of the countries under scrutiny. One source of labor market frictions is strict employment protection legislation on permanent contracts, which is associated with a stronger use of temporary contracts. To capture temporary contracts associated with strong employment protection legislation, this study uses the incidence of involuntary reallocations in and out of temporary employment at the regional level.

The first step of this study is to investigate whether labor market frictions condition the employment response of the manufacturing sector. The findings indicate that higher labor market frictions exacerbate the impact of import competition from China on manufacturing employment shares relative to the working-age population. In magnitude, the adverse impact of Chinese import competition on manufacturing employment is larger in Europe compared to the United States. One potential explanation is that employers in Europe only adjust in terms of employment as this study finds no impact of import competition on wages, independent of the level of labor market frictions. However, for the United States previous research found negative wage effects of Chinese import competition, meaning that employers adjust on both margins, employment and wages.

The second contribution of the study is to examine whether any sector of activity absorbs the detrimental impact on the manufacturing sector, or whether displaced manufacturing workers become unemployed or drop out of the labor force. Other sectors in the economy are indirectly affected by Chinese import competition for two reasons. First, the sectors get access to cheaper goods, which may lead to higher demand in labor if the demanded goods are complementary to labor. Second, labor supply choices of displaced workers change, they can choose not to supply labor any more or choose to supply labor to another sector in the economy.

In order to determine whether a particular sector or non-employment alternative absorbs the detrimental impact on the manufacturing sector, the paper repeats the same analysis as for the manufacturing sector for private services, construction, public services, the unemployment rate and the labor force participation rate. The results show that the public services sector, which encompasses health and education occupations, rises the most with higher import exposure. Other sectors of activity, such as construction, do not show any significant response due to Chinese import competition.

These findings are relevant because they show that labor market frictions matter when the economy faces import competition from low-income countries. Therefore, policymakers should try to reduce labor market frictions with carefully designed labor market institutional settings. Further, policymakers need to consider how to support workers who do not benefit from globalization, either in the form of moving or retraining subsidies.

Lastly, Chapter 5 offers a conclusion.

Chapter 2

Labor Market Polarization and Intergenerational Mobility: Theory and Evidence

2.1 Introduction

The "American Dream" allows everyone to be successful regardless of their geographic and family background. However, the United States has turned into one of the least socially mobile countries among advanced economies, and with stark differences within the United States. Chetty et al. (2014) provide evidence of large differences in upward mobility across US commuting-zones ranging from the most mobile to the least mobile among developed countries. Since the 1980s, many advanced economies including the United States have experienced strong labor market polarization. It is defined as the decline in routine occupations and the simultaneous rise of both low-income manual and high-income abstract employment. Autor and Dorn (2013) show that the decline in routine employment also depends on local factors.

This paper establishes a causal relationship between labor market polarization and intergenerational mobility. Labor market polarization can lower equality of opportunity for children from a low-income background via two channels, namely labor supply and labor demand. The first mechanism relates to educational choice, where the highest level of education yields the largest returns, i.e. the wage of an abstract job, but also incurs the highest institutional cost. Children from low-income families are less able to finance college tuition or they are more reluctant to take up a loan to pay for college education. These limited financial resources imply that they opt for either routine or manual jobs. The former also incurs an institutional cost, and considering declining wages (together with falling employment) of routine occupations, obtaining secondary education for taking up routine employment reduces lifetime utility. Therefore, labor market polarization influences education choices of younger generations.

The second channel refers to labor demand, i.e. how many jobs in routine occupations will be lost due to the acquisition of computer capital. Jaimovich and Siu (2012) implicitly provide evidence for the labor demand channel by showing that in all recessions since 1991 jobless recoveries are strongly related to the decline in routine employment.

Along the same line, Hershbein and Kahn (2018) use vacancy-postings and show that the demand for routine skills falls and confirms with the interpretation of firms restructuring of production toward routine-biased technologies and higher-skilled workers. The influence of business cycle fluctuations on routine employment and the evidence from vacancy postings is in line with a changes in changing demand for task types.

To fully understand the implications of labor market polarization on equality of opportunity across the income distribution, I set up a simple model drawing on existing models for educational choice and labor market polarization. The model builds on the standard features of the task framework from Autor et al. (2003) and more formalized in Autor and Dorn (2013). The final tradable good is produced with three types of labor, namely manual, routine and abstract, and it features substitutability between routine labor and capital. Over time, labor market polarization is driven by an exogenous decline in the price for capital as in Davis et al. (2020). In order to capture spatial patterns, I assume exogenous local productivity differences, which allows me to further characterize regions in terms of population size, and how locations differ in their degree of labor market polarization.

Households are characterized by an overlapping-generations (OLG) model with educational choice similar to Maoz and Moav (1999). I assume that individuals are upward mobile if they choose a higher level of education than their parents as returns to education rise with educational levels. Congruent with the task framework, I assume three levels of educational attainment, which differ in their costs. Individuals face educational frictions to attain education, such as ability. The education choice depends on parental transfers and future wages in each sector. The latter is crucial to understand education decisions in the face of labor market polarization, which reduces routine wages, and therefore returns to secondary education. Keane and Wolpin (2001) highlight the importance of parental transfers for the young generation to finance educational attainment. Further, they help to understand which increasingly individuals choose primary and tertiary education.

The model delivers multiple testable predictions with respect to intergenerational mobility across time and space via educational choices. As the price for capital, and hence routine wages, falls over time, the model predicts less occupational cross-generational transitions for children whose parents work in either manual or abstract occupations, and more transitions in both directions for children whose parents work in routine occupations in all locations. This translates into less upward mobility for children from parents in manual occupations. High productivity pushes up wages in all occupations, therefore population is larger in more productive locations, which in turn raises housing prices until real wages are equalized across space. Consistently, routine employment is higher in more productive regions, creating a stronger incentive to destroy routine jobs. Therefore, high-productivity locations demand more capital, and experience stronger labor market polarization, and therefore lower upward mobility. As upward mobility is defined as a cross-generational transition if a child acquires a higher level of education than their parent, these model predictions imply that labor market entrants increasingly choose “polar” educational attainment.

In the next step, I confront the main model predictions with the data. First, I test the key prediction that labor market polarization reduces intergenerational mobility across space. Exploiting commuting-zone variation, I identify the causal impact of labor market polarization on intergenerational mobility using an instrumental variable specification, which allows me to circumvent various issues of endogeneity. Based on the model and previous findings by Autor and Dorn (2013), I use historical density and routine intensity as instruments for labor market polarization. I take data on intergenerational mobility from Chetty et al. (2014) and use absolute upward mobility as a benchmark measure because it concentrates on outcomes for children from the 25^{th} percentile of the parental income distribution. In line with theoretical predictions, empirical evidence suggests that labor market polarization significantly reduces intergenerational mobility for children from low-income parents.

To test whether the key model prediction holds over time, I estimate the intergenerational elasticity (IGE) depending on parental occupational background using the Panel Study of Income Dynamics (PSID). Specifically, I estimate IGE for children whose parents work in manual, routine or abstract occupations based on the definitions by Autor and Dorn (2013). The results confirm the model predictions, namely a higher IGE for children with parents in manual and abstract occupations, while it is lower when parents work in routine occupations. This is because children with parents in routine jobs, i.e. the middle class, experience more cross-generational transitions and are more probable to enter either manual or abstract employment. Importantly, this pattern develops over time, and first emerges after the investment boom in capital during the 1990s. These findings are in line with “stickiness” among the richest and poorest in society as found by Blanden et al. (2004) for Britain and the U-shaped pattern of intergenerational mobility for the US found by Palomino et al. (2018).

In the last step of the empirical exercise, I confirm that educational attainment is polarizing over time, that it is geographically linked to labor market polarization and depends on family background. I start by showing that education became more polarized in the United States between 1970 and 2018 among labor force participants between 20 and 29 for the United States as a whole. The major increase in educational polarization occurs between 1990 and 2000, which also coincides with the investment boom in capital in the form of information and communication technology. Next, I use the PSID to compute family premia based on Checchi et al. (2013) and polarization indices for various degrees based on parental backgrounds. Third, I exploit variation across time and commuting-zones to show that labor market polarization increases educational polarization. Last, using the Current Population Survey (CPS), I estimate a linear probability model, which provides evidence that educational stickiness is stronger if labor market polarization increases.

The results indicate that a one percentage point increase in labor market polarization decreases the expected rank of children whose parents are at the 25$^{\text{th}}$ percentile of the income distribution by .57 ranks in the national income distribution. This is a sizeable economic effect of labor market polarization on intergenerational mobility as children in commuting zones without labor market polarization would be ranked 4.42 percentiles higher than children from the median-hit commuting zone. This roughly translates into 13.79% higher incomes, which is equivalent to nearly 3600 USD.[1]

Labor market polarization of wages and employment driven by automation is closely linked to income inequality as argued by Acemoglu and Restrepo (2020). Krueger (2012) and Corak (2013) highlight the negative link between income inequality and intergenerational mobility, a relationship known as the Great Gatsby curve. It holds across countries and within the United States over time. This relationship is relevant because it implies that higher inequality, usually measured with the Gini coefficient, magnifies the "persistence in the advantages and disadvantages of income passed from parents to the children". At the same time, stronger labor market polarization is also associated with widening wage inequality. However, the underlying mechanisms how income inequality impacts upward mobility are opaque.

Linking labor market polarization to intergenerational mobility has two major advantages over the link between income inequality and social mobility. First, the Gini coefficient is an annual snapshot of inequality, when, as noted already by Sahota (1978), most policy advice to reduce income disparities is concerned with lifetime inequality. Huggett et al. (2011) find that initial conditions (as of age 23) account for 61.5% of lifetime earnings, confirming that policy should focus on affecting early decisions to accumulate human capital. Labor market polarization, compared to inequality as an outcome variable, directly affects the decision of human capital investment towards either high-or low-skill education, which implies higher lifetime inequality. In the same vein, Dabla-Norris et al. (2019) show that especially young workers have to adjust to the evolution of labor markets.

The second advantage of using labor market polarization over income inequality refers to the differences in quality of jobs associated with low- and high-skilled employment. The quality of jobs encompasses a multitude of different characteristics, Osterman and Shulman (2011) argue that quality of jobs is also polarized, with "good" jobs providing anywhere from living to astronomically high wages, benefits, opportunities for advancement and training, and "bad", dead-end jobs without career-progression possibilities and paying minimum or near-minimum wages. They claim that about 25% of all jobs in the United States are "bad" jobs. Major et al. (2019) also mention the changing nature of jobs, i.e. they refer to jobs in the gig economy, which has created millions of manual jobs often done by the solo self-employed, lacking security, progression or rights. Harrison

[1] See Chetty and Hendren (2018b).

and Bluestone (1990) argue that the introduction of new management practices, which focuses on making labor, in particular low-skill labor, a more variable factor of production fostered wage polarization in the United States.

A large recent literature focuses on various explanations of intergenerational mobility, in particular sparked by Chetty et al. (2014). The authors sort factors which have been associated with intergenerational mobility in the literature into various categories. The availability of intergenerational mobility within the United States provided by the Equality of Opportunity Projects sparked a surge in estimating causal impacts of factors associated with upward mobility. A non-exhaustive list of this research includes Chetty and Hendren (2018a) and Chetty and Hendren (2018b), who investigate the impact of neighborhoods on children outcomes and find strong childhood exposure effects. Gallagher et al. (2019) identify the importance of family structure. Sharkey and Torrats-Espinosa (2017) examine how exposure to violent crime reduces intergenerational mobility. Andrews et al. (2017) show that areas with higher historical racial segregation exhibit lower levels of upward mobility.

This study contributes to the rising literature investigating the determinants of intergenerational mobility by investigating the role of labor market polarization and automation. Rothstein (2019) focuses on the quality of schools and their effect on intergenerational mobility, but finds little evidence that school quality plays a significant role. He concludes that the structure of local labor markets is a likely factor influencing economic mobility.[2] Tan (2019) provides evidence that labor markets matter historically, in particular industrial job opportunities were important drivers of upward mobility in the early 20$^{\text{th}}$ century.

This paper is closest to Adão et al. (2020), who focus on two margins of adjustment to technological progress, namely a within-generation reallocation of labor and cross-generational adjustments in the skill distribution. They provide evidence that the recent trend of innovations towards cognitive occupations affected the young generation stronger. They highlight that technological transitions are slower and more unequal if innovations are directed towards skills which are not abundant in the contemporaneous labor force. The main difference between the two papers is that I focus on the impact of the young generation across the parental income and skill distribution, and analyze how labor market polarization - driven by automation - impacts various labor market outcomes of children from different parental backgrounds, specifically educational choice and intergenerational mobility.

In the next section, I outline the theoretical framework combining existing models of educational choice and labor market polarization. Section 2.3 presents all data sources used in the empirical analysis, in particular the Decennial Censuses, the Panel Study of Income

[2] He also mentions job networks and marriage markets as other determinants of intergenerational mobility.

Dynamics, and the data on intergenerational mobility by Chetty et al. (2014). Section 2.4 takes the model predictions to the data. Section 2.5 concludes.

2.2 Theoretical framework

In this section, I build a model incorporating the task framework as in Autor and Dorn (2013) into an overlapping-generations model where individuals choose their education as in Maoz and Moav (1999). The model features the substitutability between routine labor and capital, and exogenous location-specific productivity differences. Individuals choose between three levels of educational attainment, and their education decision depends on parental bequests and future wage ratios. Primary education allows individuals to work in manual employment, secondary education in routine employment, and tertiary education in abstract employment.

The key predictions of the model relate to how labor market polarization affects educational choice, and therefore intergenerational mobility, across time and space. First, as the price for capital is declining exogenously over time, individuals from all backgrounds are less likely to choose secondary education. Therefore, the share of routine employment declines over time, while the employment shares of manual and abstract labor increase. The second key prediction applies to regional variation in labor market polarization due to idiosyncratic demand for capital. Exogenously more productive locations demand more capital, and therefore labor market polarization is stronger. As a consequence, the adverse impact on children from low-income parents is stronger in more productive regions.

2.2.1 Production technology

The economy produces a final good in every period t combining labor of three different skill-levels and capital. The good is tradable at no costs across locations, and is produced with the following production technology:

$$A_j F(L_{mjt}, L_{rjt}, L_{ajt}, K_{jt}) = A_j \left[A_m L_{mjt}^{\gamma_m} + (A_r L_{rjt}^{\theta} + A_k K_{jt}^{\theta})^{\frac{\gamma_r}{\theta}} + A_a L_{ajt}^{\gamma_a} \right], \tag{2.1}$$

where A_j denotes total productivity in location j, and A_i represents factor-augmenting technology for employment type $i \in \{a, m, r\}$, where a stands for abstract (high-skill), m for manual (low-skill) and r for routine (middle-skill). L_{ijt} indicates employment of type i in region j at time t. The fourth factor of production is capital K_{jt}, which also provides routine tasks. To assure substitutability between routine labor and capital, it must hold that $\gamma_r < \theta$. Capital often refers to information and communication technology (ICT), and encompasses both hardware and software.

The production of capital (K_t) is analogous to Davis et al. (2020), and is produced using the following technology:

$$K_t = \frac{1}{\zeta_t} Q_t, \tag{2.2}$$

where Q_t is the amount of final goods and ζ_t is a technology parameter. Perfect competition for the intermediate good implies:

$$p_{kt} = \zeta_t \tag{2.3}$$

The technology parameter, and hence the price of ICT capital, declines exogenously over time. Unsurprisingly, a lower price for capital induces a larger capital stock in the economy, as $\frac{\partial K_t}{\partial \zeta_t} < 0$. For simplicity I assume that capital as an intermediate good fully depreciates every period.

As Davis et al. (2020) explain, the intermediate good K_t has two interpretations: first, it is a capital good that substitutes for middle-paid labor as in Autor and Dorn (2013). With this view, ζ_t is a parameter that governs the efficiency of producing the capital good. The second interpretation is that K_t is an imported intermediate and ζ_t then denotes the terms of trade. As a result, a drop in p_{kt} could be either due to routinization, i.e. a drop in the price of computer capital, or due to offshoring, i.e. a drop in the domestic price of the intermediate import due to technical progress abroad or the removal of trade barriers.

All firms are price-takers and do not affect wages. Wages are determined simultaneously for all skills i and all locations j. The price of capital is governed by the exogenous technology parameter ζ_t. The firm's profit maximization problem takes on the following form:

$$\max_{L_{ijt} \forall i} \quad A_j F(L_{mjt}, L_{rjt}, L_{ajt}, K_{jt}) - \sum_{L_{ijt} \forall i} w_{ijt} L_{ijt} - p_{kt} k_{jt}, \tag{2.4}$$

where the first-order conditions (FOCs) of each labor type and capital are equal to the respective wage and the price of capital, respectively. The constraint is that each labor type and capital are greater or equal to zero, i.e. $L_{ijt} \geq 0 \; \forall \; i$ and $K_{jt} \geq 0$.

I derive the FOCs for each employment type (L_{ijt}) and capital (K_{jt}), which hold in each location j:

$$w_{mjt} = A_j \gamma_m A_m L_{mjt}^{\gamma_m - 1} \quad \forall j \tag{2.5a}$$

$$w_{rjt} = A_j \gamma_r (A_r L_{rjt}^{\theta} + A_k K_{jt}^{\theta})^{\frac{\gamma_r - \theta}{\theta}} A_r L_{rjt}^{\theta - 1} \quad \forall j \tag{2.5b}$$

$$w_{ajt} = A_j \gamma_a A_a L_{ajt}^{\gamma_a - 1} \quad \forall j \tag{2.5c}$$

$$p_{kt} = A_j \gamma_r (A_r L_{rjt}^{\theta} + A_k K_{jt}^{\theta})^{\frac{\gamma_r - \theta}{\theta}} A_k K_{jt}^{\theta - 1} \quad \forall j. \tag{2.5d}$$

The FOCs in equations (2.5a) to (2.5c) reveal that wages of each skill type i depend on four factors. First, on location-specific exogenous productivity A_j. Second, on the output elasticity of each labor type γ_i. Third, the skill-specific productivity parameter A_i, and fourth, on labor input of the specific skill L_{ijt}. Additionally, the wage of routine workers also depends on the capital stock. Due to the substitutability between routine labor and ICT capital ($\gamma_r < \theta$), a rising capital stock decreases returns to routine tasks.
Manual and abstract wages are unaffected by falling capital prices. While the substitutability between routine labor and capital is common to the literature on labor market polarization, it is more divided on how ICT capital affects the wages of extreme skills. Autor and Dorn (2013) assume complementarity between computer capital and abstract labor, Davis et al. (2020) indicates complementarity of capital with both high and low-skilled workers. vom Lehn (2019) allows for the most flexible specification with three nests in the CES production function. He argues that ICT capital is complementary to abstract labor, and that the relationship of manual employment with other employment types is more ambiguous. For simplicity, I follow Eeckhout et al. (2019) and assume that ICT capital has no impact on manual and abstract wages.

2.2.2 Education decision

Each household consists of one parent and one child, and each individual lives for two periods. Individuals gain utility from consumption in the first period, and from consumption, housing and bequests to their children in the second period.[3] Workers of all types are perfectly mobile across regions without migration costs, implying utility equalization for a given type across locations. All individuals have the same preferences according to the log-linear utility function:

$$U_{ij} = log\, U_{ijt} + log\, U_{ijt+1}, \text{ where} \tag{2.6}$$

$$U_{ijt} = c_{ijt}, \text{ and} \tag{2.7}$$

$$U_{ijt+1} = c^{\alpha}_{ijt+1} h^{\beta}_{ijt+1} x^{1-\alpha-\beta}_{ijt+1} \tag{2.8}$$

where c_{ijt} and c_{ijt+1} denote consumption of an individual i born in period t and living in region j in the two periods of her life (t and $t+1$), h_{ijt+1} represents housing costs and x_{ijt+1} illustrates the transfer to her child. The bequest motive does not differ between the different types of individuals. Relaxing this assumption would reinforce the results of the

[3] I am using the terms "bequest" and "parental investment" synonymously. This is because the former is used in the previous literature, but it can also be interpreted as the latter because education takes place during the first period in life, hence parents need to invest the money at the beginning of the first period, not at its end.

model.[4]

In the first period, individuals receive parental bequests from which they finance current consumption and their education. Similar to Maoz and Moav (1999) and Owen and Weil (1998), financial markets where individuals can borrow to finance higher levels of education are absent. This is in line with the argumentation by Tobin (1982) that lenders do not accept future human capital as collateral. In the second period, households obtain a wage according to the education they obtained in the first period and divide their labor income between consumption, housing and bequest to their children. Hence, households face the following budget constraints:

$$x_{ijt} = c_{ijt} + \delta_i \tau_{ijt} \tag{2.9a}$$

$$w_{ijt+1} = c_{ijt+1} + p_{jt+1} h_{ijt+1} + x_{ijt+1}, \tag{2.9b}$$

where δ_i symbolizes institutional costs for the three different types of education, and τ_{ijt} indicates individual educational frictions.[5] Hence, total education costs depend on institutional costs and individual educational frictions.

Individual educational frictions raise the costs of educational frictions and are paid in the form of first-period consumption. They can be thought of as a function of various factors, e.g. inverse ability as in Maoz and Moav (1999) and Abraham (2008), informational constraints, family support and engagement as highlighted by Mayer et al. (2019), preferences, or access to funding.[6] For simplicity, and in line with Papageorge and Thom (2020), individual educational frictions are independent from parental background. Relaxing this assumption and allowing for a positive relationship between parental investment (reflecting parental income) and individual educational frictions would reinforce the results obtained below. The distribution of educational frictions is constant across locations and time. For simplicity, I assume that educational frictions τ_{ijt} are uniformly distributed (within and across cities) in the interval $(\underline{\tau}_{ijt}, \bar{\tau}_{ijt})$, where $\underline{\tau}_{ijt}$ equals minimum educational frictions, and $\bar{\tau}_{ijt}$ indicates maximum education frictions. The higher educational frictions, the stronger the payment towards educational attainment in the form of consumption in the first period.

[4] Empirical evidence that high-income parents have a higher bequest motive is shown by e.g. Menchik and David (1983), and I show below that parents with higher incomes provide more support to their children.

[5] Usually, models considering intergenerational mobility and educational choice consider only two types of education, namely unskilled vs. skilled. One notable exception is Fender (2005), who extends the standard framework by considering self-employment and by introducing a third period, giving agents the chance to choose a sector of work over two periods of their lives.

[6] Albeit I abstract from this issue in the model, educational frictions can also be driven by lower access to higher education as highlighted by Hillman (2016).

Institutional costs take on the following form:

$$\delta_i = \begin{cases} 0 & \text{individual acquires primary education} \\ 1 & \text{individual acquires secondary education} \\ z & \text{individual acquires tertiary education,} \end{cases}$$

where I assume that primary education does not incur costs, which holds in advanced economies as compulsory basic education is provided freely and equally to all children. Let $z > 1$ denote the time-invariant cost of tertiary education relative to secondary education. Importantly, there are no differences in educational quality by region.
There is no uncertainty in receiving the according wage of household i in the second period of her life, for which the individual gets an education during the first period. For notational purposes, it is important to mention that the level of educational frictions (τ_{ijt}) is the only parameter in the model, which varies across individuals. As soon as an individual has sorted herself into one level of education, and implicitly occupational group, workers are identical within each group. Therefore, I denote i for each group instead of for each individual household. Future labor earnings are:

$$w_{ijt+1} = \begin{cases} w_{mjt+1} & \text{if } \delta_i = 0 \\ w_{rjt+1} & \text{if } \delta_i = 1 \\ w_{ajt+1} & \text{if } \delta_i = z, \end{cases}$$

where, as before, m, r and a represent the different types of labor in production, namely manual, routine and abstract, respectively.
Since the utility function is separable and there are no capital markets, the individual's maximization of utility can be done backwards in two stages. First, the individual decides on how to allocate her labor income in the second period between consumption, housing and bequest, and then the individual decides on the level of human capital in the first period. The second period maximization implies solving:

$$z(w_{ijt+1}) \equiv max(c^{\alpha}_{ijt+1} h^{\beta}_{ijt+1} x^{1-\alpha-\beta}_{ijt+1}) \quad \text{s.t.}(2.9b)$$

The maximization of the second period yields the respective equilibrium allocation of resources, with $c^*_{ijt+1} = \alpha w_{ijt+1}$, $x^*_{ijt+1} = (1-\alpha-\beta) w_{ijt+1}$ and $h^*_{ijt+1} = \frac{\beta w_{ijt+1}}{p_{jt+1}}$. Plugging these results back into $z(w_{ijt+1})$ gives the indirect utility for the second period. Due to perfect labor mobility, utility is constant across locations in every period. In what follows, for notational simplicity I will compare two cities instead of a number of J cities, but the results hold without loss of generality. Using the result for optimal housing expenditure

(h^*_{ijt+1}), I can show that wage ratios across cities relate:

$$\frac{w_{i1t}}{p_{1t}^{\beta}} = \frac{w_{i2t}}{p_{2t}^{\beta}} \quad \forall \quad i \in (m,r,a). \tag{2.10}$$

Equation (2.10) indicates that real wages for a given occupational group are constant across cities. This finding and the assumption of no migration costs allow me to concentrate on educational choice of individuals *within* a location and to concentrate on nominal income differences between occupations.
Individuals face two simultaneous choices about educational choice, namely whether to choose primary, secondary or tertiary education. To determine the "marginal" individual, i.e. the individual which is indifferent between choosing between two levels of educational attainment, I always compare lifetime utility for two education levels. This yields two thresholds of educational frictions for each parental background, and hence I obtain six six thresholds of educational frictions in total. I use the optimal allocation of resources in the second period and plug them into the utility functions from equation (2.6) and exploit equation (2.9a) in order to determine the educational choice. To illustrate the choice problems individuals face, I illustrate two choice problems. Children whose parents work in a manual job, and who choose between primary and secondary education. She will choose secondary education, i.e. routine employment, if and only if:

$$log\,(x_{mjt} - \tau_{ijt}) + log\, w_{rjt+1} \geq log\, x_{mjt} + log\, w_{mjt+1}.$$

Analogously, a child whose parents in routine employment, and who chooses between secondary and tertiary education. She will choose tertiary education if and only if:

$$log\,(x_{rjt} - z\tau_{ijt}) + log\, w_{ajt+1} \geq log\,(x_{rjt} - \tau_{ijt}) + log\, w_{rjt+1}.$$

From these two examples of the six choice problems, it follows that she will invest in the higher level of educational attainment if educational frictions τ_{ijt} are small enough, i.e. if educational costs are not too high. Let $\hat{\tau}_{ijt}$ denote the critical value of educational frictions for the marginal individual i, i.e the individual indifferent between the two choices. The six thresholds take on the following form:

$$\hat{\tau}_{ijt}^{mr} = x_{mjt}\left[1 - \frac{w_{mjt+1}}{w_{rjt+1}}\right], \tag{2.11}$$

$$\hat{\tau}_{ijt}^{ma} = \frac{x_{mjt}}{z}\left[1 - \frac{w_{mjt+1}}{w_{ajt+1}}\right] \tag{2.12}$$

$$\hat{\tau}_{ijt}^{rm} = x_{rjt}\left[1 - \frac{w_{mjt+1}}{w_{rjt+1}}\right], \tag{2.13}$$

$$\hat{\tau}_{ijt}^{ra} = \frac{x_{rjt}\left[1 - \frac{w_{rjt+1}}{w_{ajt+1}}\right]}{z - \frac{w_{rjt+1}}{w_{ajt+1}}} \tag{2.14}$$

$$\hat{\tau}_{ijt}^{am} = \frac{x_{ajt}}{z}\left[1 - \frac{w_{mjt+1}}{w_{ajt+1}}\right] \tag{2.15}$$

$$\hat{\tau}_{ijt}^{ar} = \frac{x_{ajt}\left[1 - \frac{w_{rjt+1}}{w_{ajt+1}}\right]}{z - \frac{w_{rjt+1}}{w_{ajt+1}}}, \tag{2.16}$$

where the first letter of the superscript indicates the occupation in which the individual's parents worked, and the second letter where the individual works in the second period. For example, in equation (2.11), the individual's parents worked in manual employment, and the individual chooses routine employment if her level of educational frictions is below the threshold value $\hat{\tau}_{ijt}^{mr}$. I define "upward mobility" with respect to education - and hence implicitly for occupation and income - if the individual chooses a higher level of education than her parents. Downward mobility is defined as the case where the individual chooses a lower level of educational attainment than her parents.

All thresholds of individual educational frictions are expressed as a function of future wages and of the transfer received individual received from her parents. The components of the threshold functions are similar to Maoz and Moav (1999), Owen and Weil (1998) and Galor and Tsiddon (1997). The inclusion of future wages implies perfect foresight of how wages develop in the future with declining price for capital. Parental transfers play a crucial role in educational choice. This finds empirical support by Keane and Wolpin (2001), and I also provide evidence for stronger financial support by more affluent parents in the empirical section.

I conduct a comparative statics analysis in order to understand how parental bequests and future wages affect the thresholds of educational frictions. Note that the threshold is continuous and differentiable with respect to parental investment x_{ijt}, and future wages. Consider w_{ijt+1} the wage for the employment type which requires a relative lower level of educational attainment (numerator), and $w_{i'jt+1}$ the wage for the employment type which requires a higher level of educational attainment (denominator). The comparative statics reveal the following: $\frac{\partial \hat{\tau}_{ijt}}{\partial x_{ijt}} > 0$, $\frac{\partial \hat{\tau}_{ijt}}{\partial w_{ijt+1}} < 0$ and $\frac{\partial \hat{\tau}_{ijt}}{\partial w_{i'jt+1}} > 0$. In words, these findings imply that higher bequests and a rising wage in i' raise the threshold of educational frictions, implying that the marginal individual faces higher constraints. This, in turn, means that upward mobility is more likely to occur as more individuals will enter the sector requiring a higher level of education. On the other hand, if wages in i are rising, then the marginal individual has a lower level of educational frictions, and thus less upward mobility takes place.

When tertiary education, i.e. working in abstract employment, constitutes one side of the choice problem, then the threshold function of individual educational frictions also includes the costs of tertiary education z. The derivative sign of each threshold including these costs is negative with respect to z, i.e. $\frac{\partial \hat{\tau}_{ijt}}{\partial z} < 0$. This comparative static indicates that the marginal individual has a lower level of educational frictions τ_{ijt} if the costs of tertiary education are rising. In other words, upward mobility (from parents with either manual or routine employment) is more difficult if the cost of tertiary education is high.

2.2.3 Upward and Downward Mobility

The model predicts how intergenerational mobility changes due to rising automation of routine tasks varies in two dimensions, namely across time and space. The first dimension emerges because the technology parameter ζ_t falls exogenously over time. The declining price for ICT capital implies a rising capital stock in the economy. As ICT capital performs routine tasks, this development has a detrimental impact on routine wages. Therefore, the returns to secondary education fall, while a higher capital stock does not directly affect the returns to primary nor tertiary education, i.e. manual and abstract employment, respectively. In the choice problem of educational attainment, the wage ratios between different task types matters and influences the level of individual educational frictions.

Proposition 1 ***Polarization over Time*** *Assume substitutability between routine labor and capital, i.e. $\gamma_r < \theta$. Substitutability implies $\frac{\partial w_{rjt}}{\partial K_{jt}} < 0 \, \forall j$. Then educational choice of individuals polarizes over time as the capital stock increases because $\frac{\partial \hat{\tau}^{mr}_{ijt}}{\partial w_{rjt}} > 0$ and $\frac{\partial \hat{\tau}^{rm}_{ijt}}{\partial w_{rjt}} > 0$, and $\frac{\partial \hat{\tau}^{ra}_{ijt}}{\partial w_{rjt}} < 0$ and $\frac{\partial \hat{\tau}^{ar}_{ijt}}{\partial w_{rjt}} < 0 \, \forall j$. The first two derivatives indicate that falling routine wages induces more individuals whose parents work in either manual or routine employment to acquire primary education instead of secondary education. The latter two derivatives indicate that falling routine wages induces more individuals whose parents work in either routine or abstract employment acquire tertiary education instead of secondary education.*
Proof see Appendix 2.A.

The second dimension concerns difference in cross-generational transitions in education, and therefore occupational type and income, across space. The underlying idea is to determine whether demand for capital is location-specific. Locations only differ by their exogenous productivity level A_j, i.e. some locations have a higher absolute advantage across all employment types. As argued before, the locations-specific productivity parameter is a determinant of wages for all skill types. Before turning to the actual prediction of interest, I derive a key property as to how locations differ due to differences in absolute advantage in production of the final good, which I will also exploit in my empirical analysis. As noted above, I will compare two cities instead of a number of J cities without a loss of generality. In what follows, I always assume that productivity in location 1 is higher than in location 2, i.e. $A_1 > A_2$.
This property concerns the population size (and density) of different locations. The local population is equal to the sum of labor demands for all three employment types in all locations. This is due to the assumption that every individual in the second generation is in employment.[7] It is directly visible in Appendix 2.B that labor demand for both manual

[7] Due to the assumption of two members in each household (young and old) in every period, children do not change this model prediction.

and abstract labor are higher in the more productive location, i.e. location 1. In order to determine location size, the crucial part is to identify where labor demand for routine occupations is higher. After a proof via contradiction, it is clear that the demand for routine occupations is higher in location 1 as well. Subsequently, as all labor demands are higher in the more productive location, this region is also larger in terms of population. Assuming the same area for all locations, a higher population size in a region translates directly in higher density in the same location.

Proposition 2 ***Population Size*** *Assume* $\gamma_r < \theta$. $A_1 > A_2 \rightarrow S_1 > S_2$, *i.e. population in location* 1 *is larger than location* 2. *Given the assumption that area size is equal across regions, then location* 1 *exhibits higher density than location* 2.
Proof see Appendix 2.D.

Now I turn to the second dimension how intergenerational mobility is heterogeneous across space due to idiosyncratic demand for capital. From Proposition 1, I know that a rising capital stock in the economy reduces cross-generational transitions with respect to education, occupation and income. If the demand for capital is location-specific and related to the previous three properties, then the location demanding more capital will experience stronger polarization in educational choice than the location demanding less ICT capital.

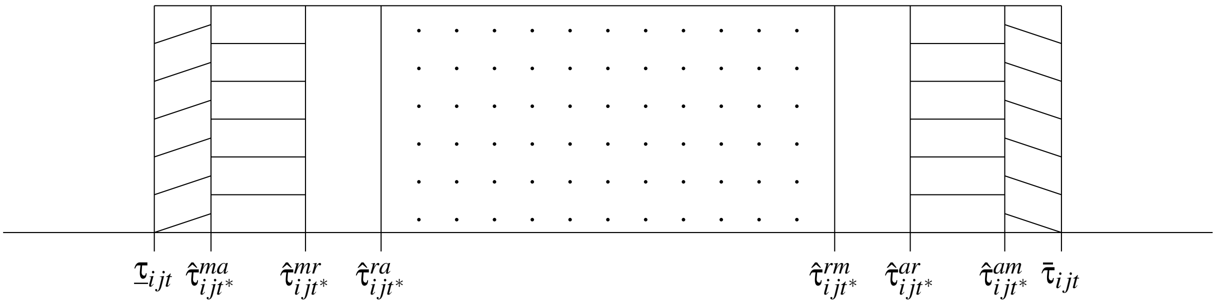
Proposition 3 *(Polarization across Space) Assume* $\gamma_r < \theta$. $A_1 > A_2 \rightarrow K_{1t} > K_{2t}$, *i.e. location* 1 *demands more capital, and therefore experiences stronger polarization in educational attainment than location* 2.
Proof see Appendix 2.E.

The model predicts higher demand for capital for the more productive and more populous region. This is driven by the combination of substitutability between routine labor and capital and a larger absolute number of routine workers in the more populous location. The latter result formulated in Proposition (2) implies that there is greater potential for substitution between routine labor and capital in the larger location. In line with Davis et al. (2020), relative exposure is not the key driver that explains the destruction of middle-paid jobs in a given location. Instead, the falling price of computer capital is a necessary condition for the destruction of routine employment, but it is not sufficient. The sufficient condition is that there needs to be an incentive to destroy these jobs. In the model, the incentive to destroy middle-paid jobs depend on regional characteristics, primarily higher absolute advantages across all task types. The higher absolute advantage also manifests itself in housing prices, location size and thick tails.
Figure 2.1 shows the uniform distribution of educational frictions and the six thresholds of educational choice for two different states of the economy, one with a low and one

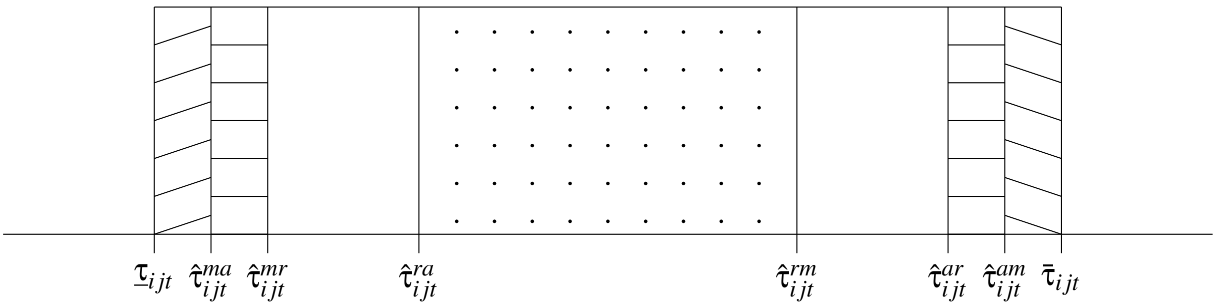
with a high capital stock. The former can reflect either the economy with a high price for capital or a low-productivity location, while the latter can be interpreted either as the economy with a low price for the intermediate good or as a location with high productivity. It reveals how the thresholds differ qualitatively based on the model predictions discussed above. The distribution of educational frictions ranges from its minimum value $\underline{\tau}_{ijt}$ to its maximum $\bar{\tau}_{ijt}$

Figure 2.1: Education Thresholds

(a) Mobility Thresholds with Low Capital Stock



(b) Mobility Thresholds with High Capital Stock



Notes: The figure depicts the thresholds of educational choice for two different levels of the of the capital stock. All six thresholds depend on parental bequests and future wage ratios. The upper panel shows the thresholds when the capital stock is low, and the latter when the capital stock is high. The thresholds indicate that more cross-generational transitions occur in the former compared to the latter. The areas with upward and downward sloping lines indicate the share of children who transition from manual to abstract and vice versa, respectively. They are unchanged in the model as capital does not impact their wage ratio. The areas with straight slopes indicate the children who transition from either manual or abstract parents into routine employment. These areas are larger in the upper panel as routine wages are falling less in a state with less capital. The dotted area indicates the share of children who do not experience cross-generational transfers out of secondary education. For the same reason, this area is also larger in the upper panel.

First, I describe how upward mobility changes with respect to education with labor market polarization for children from parents working in the manual sector. Wages in routine occupations are falling, while wages in manual employment are unchanged. This creates an incentive to *not* invest in secondary education when the rise of computer capital is stronger. Hence, the threshold $\hat{\tau}^{mr}_{ijt}$ in the lower panel of Figure 2.1 is shifted to the left compared to the upper panel. This finding implies that the marginal individual getting secondary education has lower educational frictions when the capital stock is low compared to when the capital stock is high. Consequently, upward mobility between low-

income and middle-income jobs is *lower* in the latter, i.e. in the lower panel, compared to the former, i.e. the upper panel. In both panels, the area on the left with horizontal lines between $\hat{\tau}_{ijt}^{ma}$ and $\hat{\tau}_{ijt}^{mr}$ is the fraction experiencing upward mobility from manual to routine, while the area right of the threshold $\hat{\tau}_{ijt}^{mr}$ shows the share of children taking up jobs in manual occupations because they did not afford more than basic education. Therefore, the share of children from parents in manual workers also work in manual occupations.
Children with parents in the manual occupations can also exhibit upward mobility if they attain tertiary education and earn the respective future wage. The threshold depends on how wages in manual and abstract occupations change relative to one another. However, as argued above, the wage ratio between manual and abstract employment does not change with respect to the capital stock. Hence, threshold $\hat{\tau}_{ijt}^{ma}$ is the same in both panels. Specifically, the area between $\underline{\tau}_{ijt}$ and $\hat{\tau}_{ijt}^{ma}$ with the upwardly sloped lines indicates the share of children experiencing upward mobility from manual to abstract occupations. If computer capital had an impact on wages for both types of employment, then it would depend on the relative impact. Typically, and in line with skill-biased technological change, abstract workers would profit relatively more than manual workers. Hence, the wage ratio between manual and abstract employment would fall, and by implication shift the threshold $\hat{\tau}_{ijt}^{ma}$ to the right. However, higher costs z for tertiary education can counteract this shift to the right.
Second, I examine the changing thresholds for children with parents working in routine-intensive occupations, i.e. from the "middle class". If individual educational frictions τ_{ijt} are lower than the threshold $\hat{\tau}_{ijt}^{ra}$, then a child will enter abstract employment, whereas if their individual cost is higher than critical value of $\hat{\tau}_{ijt}^{rm}$, then they enter manual employment. In the former case, they exhibit upward mobility, and in the latter they are downward mobile. With constant wages in manual and abstract employment and declining wages in routine occupations, both thresholds are shifted stronger in opposite directions when the capital stock is high. This means that children are *more mobile in both directions*. Specifically, children of parents in routine employment increasingly choose either primary or tertiary education if the capital stock is high. Both shifts are reinforced by falling bequests as equation (2.5b) shows that they are a function of routine wages for children with this background. Finally, the dotted area in both panels indicates the interval where children do not change the sector of employment relative to their parents, i.e. they stay in routine employment. This area is smaller in the lower panel where the capital stock is higher. The total amount of routine workers is the dotted area plus the two areas with horizontal lines. In the upper panel all areas are larger compared to the lower one, reflecting a decline in routine employment when the capital stock is high.
Third, the educational choice of children whose parents work in abstract occupations is analogous to children from parents in manual occupations, just vice versa. That is, they are more likely get tertiary education than secondary education for routine occupations

in location j where the demand for computer capital is stronger than in location j'. This is primarily driven by falling routine wages, but also reinforced by rising parental investment. This shifts the threshold $\hat{\tau}^{ar}_{ijt}$ further to the right in location j, indicating lower downward mobility for children whose parents work in abstract jobs. Analogously to the argumentation for threshold $\hat{\tau}^{ma}_{ijt}$, the threshold and $\hat{\tau}^{am}_{ijt}$ is the same in both cities. However, if polarization had a direct positive impact on abstract wages, this threshold would be shifted to the right as well, reflecting lower downward occupational transitions from abstract to manual wages across generations.

2.2.4 Qualifying Predictions

The model also provides predictions beyond the three key propositions mentioned in the previous section. Specifically, they refer to housing prices and "thick tails". For the former, equation (2.10) reveals that real wages, i.e. nominal wages net of housing costs, are constant across locations. Further, I know that nominal wages for all tasks depend positively on the degree of exogenous location-specific productivity from equations (2.5a) to 2.5c). Therefore, housing prices are higher in more productive locations. Appendix 2.C examines the exact relationship between the housing price ratio and the productivity ratio. The productivity ratio is larger than the housing price ratio to the power of its expenditure share. Due to the Cobb-Douglas structure of the utility function for the second period of life shown in equation (2.8), the expenditure share for housing is equal to β.

Proposition 4 ***Housing Prices*** *Assume* $\gamma_r < \theta$. $A_1 > A_2 \to p_{1t} > p_{2t}$, *i.e. housing prices in location* 1 *are higher than in location* 2.
Proof see Appendix 2.C.

Eeckhout et al. (2014) show that larger cities in the United States exhibit larger shares of extreme skills than smaller cities, which they phrase as incidence of "thick tails".[8] Similarly, Autor (2019, Fig. 7, Panel A) shows that the share of manual workers has increased in more dense commuting-zones, especially between 2000 and 2015. Eeckhout et al. (2019) show that in a similar setting, the model leads to thick tails if $\gamma_m = \gamma_r = \gamma_m = \gamma$. In words, if the output elasticity of manual, routine and abstract labor are equal, then more productive and larger region 1 exhibits thick tails. With this assumption, the model treats both input factors analogously, i.e. they are symmetric in their labor demands across locations.

My theoretical framework predicts thick tails due to individual heterogeneity with respect to educational frictions, and subsequent sorting into different occupational groups. Going back to Figure 2.1, the share of workers in manual workers is set up the following: it

[8] Davis et al. (2020) show that polarization does not occur symmetrically in France. Specifically, they show that the share of manual workers increases more in small cities, whereas the share of abstract labor is stronger in large cities.

is the sum of all children from parents working in manual employment and with educational frictions larger than $\hat{\tau}^{mr}_{ijt}$, all children from parents working in routine employment and with educational frictions than $\hat{\tau}^{rm}_{ijt}$, and all children whose parents work in abstract employment and with educational frictions larger than $\hat{\tau}^{am}_{ijt}$. Comparing the upper and the lower panel, the figure reveals that the first two addends are larger when the capital stock is higher. Therefore, the share of workers in manual occupations is rising with an increasing capital stock. The same holds for abstract employment.

Proposition 5 ***Thick Tails*** *Assume $\gamma_r < \theta$. Educational sorting due to individual heterogeneity in educational frictions (τ_{ijt}) leads to thick tails when the capital stock is high. This is driven by declining returns to secondary education and subsequent sorting into "extreme" educational attainment levels.*

Economically, the incidence of thick tails means that abstract workers profit substantially from the presence of manual workers for two reasons. First, abstract workers use administrative work or other services provided by manual workers. Second, abstract workers demand manual workers via consumption spillovers, see e.g. Manning (2004). In this framework, low- and high-skilled workers do not complement in each other in production of a single good, instead low-skilled workers do "housework" activities for high-skilled workers, but these activities require physical proximity. Independent of the underlying explanation, the model predicts colocation of "extreme" skills in large cities.

2.3 Data Sources

This section presents the various data sources used in the subsequent empirical analysis which allow me to confront the model predictions with the data. I will first present the data I exploit for the commuting-zone analyses, for which the geographic dimension of the model takes on a major role. Then I turn to the Panel Study of Income Dynamics, which I exploit for variation over time and allows me to control for parental background.

2.3.1 Commuting Zone Data

I exploit four different data sources in order to investigate whether the data confirms the model predictions. The main data source for multiple tests, such as ICT investment, educational polarization and upward mobility, are the Decennial Censuses available from IPUMS. Specifically, I use the censuses from 1970 to 2000 and the American Community Surveys (ACS) from 2010 and 2018 (Ruggles et al., 2018).[9] The data includes between 1% and 5% of the whole American population on all labor market statistics and more. From this data, I collect information on labor market polarization and other labor market

[9] I cannot use the 2010 Census because it does not include key variables, e.g. on education.

variables, e.g. routine employment shares, similar to Autor and Dorn (2013), and on educational polarization. The authors highlight that there is no established measure of labor market polarization, and exploit the share of non-college service employment. I focus on the decline in routine employment, but also show results for upward mobility on non-college service employment. I compute changes in employment structure between 1990 and 2010 as the income in Chetty et al. (2014) is measured in the two years after 2010, and use the change in non-college service employment between 1990 and 2010. The data for the covariates also largely stems from the same data sources.

For upward mobility, I exploit the data on intergenerational mobility by Chetty et al. (2014). The authors estimate the relationship between parental income rank and children's income with a rank-rank specification for children born in the years 1980 and 1982. For their preferred measure, absolute upward mobility, which I also use in the benchmark regressions, they just need two parameters of their estimation, namely the slope and the intercept. They focus on children whose parents are located at the 25$^{\text{th}}$ percentile of the national income distribution and estimate the expected rank of these children. To estimate intergenerational mobility they use administrative records of more than 40 million children and their parents, and provide the data for all commuting zones with more than 250 children. One strong advantage of the data is that there is no variation in method nor collection dates, income is collected in 2011 and 2012, i.e. when the children are about the age of 30 to 32. They show that intergenerational mobility exhibits significant variation across regions, ranging from levels of the most mobile countries to below that of any developed country. Two further measures the authors provide are relative mobility, which measures the difference in outcomes between children from top versus bottom income families, and the transition probability where parents are in the lowest quintile of the national income distribution and children end up in the highest quintile. Both measures are used in robustness analyses.

In order to measure density by commuting zone in 1970, I use the County Intercensal Tables 1970 to 1979 by the Census Bureau, which provide county-level population by various demographics, such as age, sex and race. In a given census years, the information on population comes directly from data collection. For the years in between two censuses, the Census Bureau estimates county population. This makes the use of 1970 more reliable than any other year from the County Intercensal Tables. I merge information on total population on the county level with land area in square miles in 1970 on the commuting-zone level. The next step comprises aggregating the county-level on population and land area to commuting zones defined by their 1990 commuting patterns with the help of the concordance table by the US Department of Agriculture. After the aggregation, I compute the (log) density for each commuting-zone. Density in 1970 varies substantially across commuting zones. The average density of a commuting-zone is just above 108 persons per square mile in 1970. In a commuting-zone at the 10^{th} percentile, slightly above 13 people live within a square mile, while at the 90^{th} slightly more than 930 live within the same area. This numbers are somewhat larger than in the overall population, but this is likely to be true because the smallest (and hence probably least dense areas) are not part of the sample as Chetty et al. (2014) require a minimum number of observations within a commuting zone.

Panel A in Table 2.1 shows descriptive statistics for the main variables crucial to the analysis and graphical representation. The first three measures give an overview of the variation of intergenerational mobility in the United States and are taken from Chetty et al. (2014). Their preferred measure, i.e. absolute upward mobility, measures the expected rank of a child whose parents are located at the $25^t h$ percentile of the national income distribution. The average expected rank is 42.57, so there is upward mobility on average, but as discussed already by Chetty et al. (2014) - considerable heterogeneity across space, seen by the standard deviation and both the 10^{th} and 90^{th} percentiles. For relative mobility, it is important to keep in mind that the higher the number, the lower upward mobility (see explanation in robustness analysis). In terms of extreme-quintile mobility, i.e. 8.7% of children whose parents are located in the bottom quintile of the national income distribution land in the highest quintile. This measures also exhibits strong heterogeneity, with the 90^{th} percentile about 2.5 times as high as the 10^{th} percentile.

The table also reports the degree of labor market polarization between 1990 and 2010. On average, the share of routine employment fell by 6.45% over this time period, with substantial heterogeneity ranging from more than 9.7% to a bit more than 2.2% shown by the 10^{th} and 90^{th} percentiles, respectively. The rise of each non-college and college service employment is similar on average, with 2.62% and 3.40%, respectively. These changes seem to indicate that a small share of the working-age population, i.e. about .5%, which was previously working in routine occupations, is not in employment because the sum of the means of the changes in the extreme skills are less than the loss in routine occupations. Further, there is strong regional variation in all three employment shares relative to working-age population. Similar to Autor and Dorn (2013), I exploit historical share of routine employment as an instrumental variable when I estimate the causal impact of labor market polarization on upward mobility. The table shows that the average share of routine employment in 1980 relative to total population is 33.63%.

I compute investment in information and communication technology (ICT) per worker on the commuting-zone level using and relate this to density and the share of population with a college degree, i.e. the "thick tails' prediction of the model. The Survey of Current Business is a quinquennial survey and it contains data on the distribution of new structures, equipment, and software from capital flow tables. However, the data does not include any geographic information, instead it contains detailed sectoral information, which I use to match it with sectoral information from the Census PUMS samples 1980 (for 1882) and 1990 (for 1992 and 1997). ICT investment per worker is measured in thousand USD with

2010 as base year. Between 1982 and 1997, average ICT investment per worker more than quadrupled in real terms. Average investment per worker rose from 8,140 USD in 1982 to 33,630 USD in 1997. Similar to the share of college degree, the commuting zone at the 10^{th} percentile invests about half as much per worker as the commuting zone at the 90^{th} percentile. This holds for all years, e.g. in 1997 the former invested 26,330 USD in ICT, while the latter spent 39,040 USD. The share of the population with a college degree in 1970 is equal to 6.08 percent, but also exhibits strong variation across commuting zones. The share of college degrees in the commuting zone at the 10^{th} percentile with 3.82% is less than half of that in the commuting at the 90^{th} percentile with 8.82%.

Table 2.1: Commuting-Zone Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	Obs.	Mean	Std. Dev.	P10	P90
		Panel A - Cross-Sectional Data			
Absolute Upward Mobility	693	42.57	4.56	37.33	47.98
Relative Mobility	693	33.38	5.87	25.00	40.07
Transition Probability (P1, K5)	693	8.70	3.77	4.90	12.43
Δ Routine Emp.	693	-6.45	3.01	-9.72	-2.21
Δ Non-College Svc. Emp.	693	2.62	1.37	0.91	4.04
Δ College Svc. Emp.	693	3.40	2.29	0.54	6.32
Log Density (1970)	693	4.69	1.69	2.58	6.84
Share College Degree (1970)	693	6.08	1.86	3.82	8.28
ICT Investment per worker (1982)	693	7.06	1.54	5.11	8.90
ICT Investment per worker (1992)	693	8.14	2.37	5.48	11.13
ICT Investment per worker (1997)	693	16.60	4.90	11.08	23.17
Routine Employment (1970)	693	36.71	6.71	27.29	45.41
		Panel B - Panel Data			
Δ Routine	2327	-3.02	2.93	-6.41	0.62
Allison-Foster	2327	2.85	0.47	2.22	3.48
ANY(2,1)	2327	0.30	0.06	0.23	0.38
ANY(1,2)	2327	0.35	0.05	0.27	0.41
ANY(4,1)	2327	0.39	0.09	0.28	0.51
ANY(1,4)	2327	0.43	0.06	0.35	0.50

Notes: The table shows summary statistics for commuting-zone variables used throughout the analysis. Panel A presents variables used in the cross-section. Cross-sectional data is used for presenting evidence of ICT investment and how it differs across commuting-zones, and for the final analysis relating labor market polarization and upward mobility. Panel B shows the decadal changes in routine employment and various metrics of education polarization between 1970 and 2018 using Decennial Censuses. The number of observations for the panel analysis is limited to those commuting zones where median education is equal to the national median as these metrics require the same median for comparability.

Panel B of Table 2.1 presents summary statistics for the panel data on the commuting-zone level used in the subsequent analysis. It shows the decadal decrease in routine employment and various measures of educational polarization between 1970 and 2018. The decrease in routine employment relative to working-age population by decade is larger than 3 percentage points, which is close to half the average value in Panel A, where the difference is 20 years. For educational polarization, I compute the five measures of educational polarization, namely the index by Allison and Foster (2004) and the indices with differential weights on the lower or upper part of the distribution by Naga and Yalcin (2008). As discussed in more detail below, one drawback applies to these measures. The values of the same index can only be compared for two different distributions if they have the same median. As Allison and Foster (2004) explain, the median is the central point of each of these measures, and serves as the reference point. Each measure takes into account the spread away from this median, and if the center changes, the spread will ultimately change, and the indices are not comparable any longer.

Due to the median-based approach of each education polarization index, the panel of commuting zones is unbalanced. This is because I have chosen to use the information on educational polarization from commuting-zones where the median education coincides with the national mode in a given year in order to get a maximum of observations with comparable polarization indices. The unbalanced panel is a result of varying medians of across commuting-zones and non-linear changes. Decadal changes in routine employment are measured from 1970 to 2018, i.e. the first difference is between 1980 and 1970, and the last between 2018 and 2010. Overall, in the United States there are 741 commuting zones, which would yield a total number of observations of 3705 if the panel was balanced. However, for the analysis I can only exploit 2327 commuting-zones, which means that I make use of around 465 commuting zones every decade in the panel.

Finally, the table shows the summary statistics for the five different measures of educational polarization. At a first glance, the previously-mentioned scaling between zero and one of the ANY(α, β) measures is apparent. Average polarization is lower if more weight is put on the upper part of the distribution reflected by a higher value of α. This can be due to the overall upskilling in the United States over the past decades as documented widely in the literature, e.g. by Castro and Coen-Pirani (2016). All indices also exhibit lower (absolute and relative) standard deviation in all educational polarization compared to the decline in routine employment relative to working-age population.

2.3.2 Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID) is the longest-running panel household survey in the United States and allows me to follow individuals over their lifetime and retrieve information about their parents with respect to income. The survey started in

1968 and was conducted annually until 1997, and since then biennial, with 2017 being the latest available data. I focus on the 'core' sample of the PSID. I focus on children who later become heads (sons and daughters) or spouses (typically daughters). I use the family and individual family codes provided by the PSID to follow sons and daughters when they leave the parental household and form their own family unit.

As is standard in the literature of intergenerational mobility, I measure total family income, which includes taxable incomes and transfers received by the head, the spouse and other family members. It is consistently included in the PSID with nominal values.[10] To account for changes in nominal income due to inflation, I transform income into 2010 US dollar by using the average consumer price index (CPI) from the Federal Reserve Bank. I account for outliers by dropping the lowest and highest percentile of parental total incomes.

Solon (2002) argues that it is important exploit the permanent income of the parents during teenagehood of children in order to estimate intergenerational elasticity. In other words, using only a single observation of parental total income during the age of 13 to 19 leads to the underestimation of intergenerational mobility because the parents' income in a single year can be subject to transitory labor market shocks. To account for this, I average total parental income when children are between 13 and 19, provided there are at least three observations of parental income during teenagehood. Income of children can also be subject to transitory shocks, that is why I mean out the children's income during adulthood over three waves.

The PSID has been used in many previous studies of intergenerational mobility. A non-exhaustive list includes Solon (1992), who was the first to exploit the PSID as a data source to estimate intergenerational elasticity (IGE). Further, Lee and Solon (2009) show that more observations from the PSID can be used by introducing quartic polynomials around a centered age, which account for the life-cycle bias. Palomino et al. (2018) uses the PSID to estimate IGE along the parental income distribution. Mazumder (2018) provides a review of the literature and how the PSID contributed to the now widely spread view that the United States is among the least socially mobile countries among developed countries. The main alternative data set for intergenerational mobility in the United States is the National Longitudinal Survey of Youth (NLSY), which has been used by e.g. Kourtellos et al. (2020). Palomino et al. (2018, Table 4) provide an overview of IGE studies including of data sources and point estimates. Typically, the point estimates using the PSID range between 0.34 and 0.51 without demographic controls, depending on sample and time period used. Usually, education reduces this estimate considerably.

[10] As the interviews are conducted throughout the year, the incomes refer to the previous year of the interview.

2.3.2.1 Descriptive Statistics

Based on the sample selection described above, the data set of children whose family income I can observe between 1980 and 2016. In total, my sample consists of 85,865 observations encompassing both sons and daughters, and where I can observe parental income during teenagehood. The total number of sons and daughters I observe is equal to 8493, implying that I observe each child of the parent-child pair on average 10.11 times. Of all children, I can also observe the occupations of all parents (if present), however in both the subsequent descriptive statistics and the analysis I will concentrate on the occupation of the head of the household, assuming that this is the parent with higher earnings during teenagehood.

Table 2.2: Summary Statistics of Panel Study of Income Dynamics

	Unemployed	Manual	Routine	Abstract
Family Income	10.56	10.84	10.90	11.16
	(0.93)	(0.81)	(0.76)	(0.79)
Parental Income	10.39	10.73	10.87	11.22
	(0.65)	(0.54)	(0.42)	(0.50)
Share Female	55.89	50.60	51.58	50.00
	(49.65)	(50.00)	(49.98)	(50.00)
Age	37.31	38.32	38.91	37.99
	(9.29)	(9.77)	(9.97)	(9.66)
Education	12.66	12.97	13.42	14.45
	(2.06)	(1.93)	(1.99)	(2.03)
Share White	60.55	79.84	81.22	91.96
	(48.88)	(40.12)	(39.05)	(27.19)
Share Black	35.73	16.03	15.78	5.56
	(47.92)	(36.69)	(36.46)	(22.91)
Share Other	3.72	4.13	2.99	2.48
	(18.92)	(19.91)	(17.04)	(15.54)
Observations	11927	26729	17269	29940

Notes: This table shows summary statistics of family incomes of both parents and children, and demographic characteristics of the children by occupational background of the family's head during the child's teenagehood. The summary statistics are means and standard deviation in brackets. Occupational background is divided into four distinct categories, i.e. unemployed, manual, routine and abstract. The latter three categories are of interest for the analysis below.

Table 2.2 shows the variable of interest, i.e. family income (in logs), by occupational background in three categories. These categories are unemployed, manual, routine and abstract. In what follows, I will concentrate on the last three categories because they reflect the occupations in the task framework by Autor et al. (2003) incorporated in the model above. Unsurprisingly, parental income rises with occupational category, i.e. average parental income of parents who work in a manual occupation is smaller than those in routine occupations, which again is smaller than parents working in abstract occupations.

This order has not changed in terms of family incomes of the children, but the gaps are somewhat smaller, while the standard deviation is much larger. One reason for the higher standard deviations could be larger within-occupation inequality as documented e.g. by Kambourov and Manovskii (2009) for United States. Besides the rise of superstar firms, e.g. Autor et al. (2020), the theory in section 2.2 offers implicitly an alternative explanation for this pattern: Due to limited intergenerational mobility, individual ability varies stronger for new generations entering different occupations.

Panel (a) of Figure 2.2 shows the quintiles of point estimates of intergenerational mobility across states based on equation (2.20) explained below. I show the results already here in order to show a comparison of regional social mobility with Chetty et al. (2014)[Fig. VI]. Two remarks are necessary for the comparison of their map and the map based on the PSID. First, public data in the PSID only provides geographic information on the state-level and not on a lower level, whereas Chetty et al. (2014) have administrative data, i.e. tax returns, which allows the authors to provide more granular estimates of intergenerational mobility. Given the comparatively small number of observations in the PSID compared to the administrative data, the likely level of aggregation of the PSID would have been on the state level as well even with the availability of more granular geographic information.

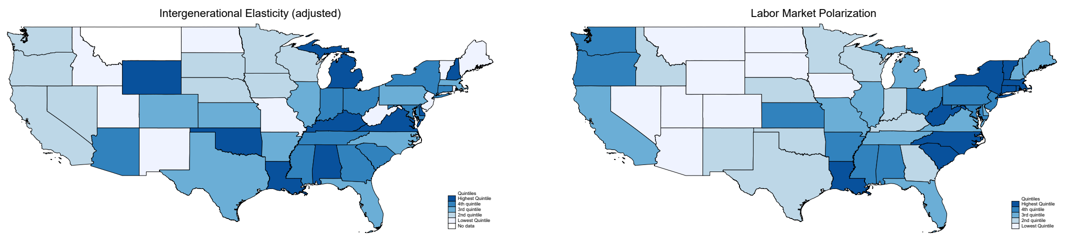
Second, the map in Chetty et al. (2014) shows absolute upward mobility, which differs from intergenerational elasticity, which I am estimating in line with previous work. Chetty et al. (2014) argue that IGE combines the dependence features captured by the rank-rank slope with the ratio of income inequality measured by their standard deviation across generations. In order to account for this bias due to diverging income inequality across generations across states, I compute both the average standard deviation during teenagehood, i.e. the same years when I measure parental income, in the state where the child spent most years during the time and the standard deviation of the state where the child is living when I observe it during adulthood. With the point estimates for state-level IGE and measurements of income inequality across generations expressed by standard deviations, I can apply Chetty et al. (2014, Eq. 1):

$$IGE = \rho_{XY} \frac{SD(logY_i)}{SD(logX_i)}, \tag{2.17}$$

where ρ is the correlation between log child income (X) and log parent income (Y) and $SD()$ represents the standard deviation of the respective generation, I obtain “adjusted” estimates of intergenerational mobility for the majority of states using the PSID.

The left panel of Figure 2.2 shows the regional distribution of adjusted intergenerational mobility in the United States in quintiles. Darker colors indicate that intergenerational elasticity is larger than in states with lighter colors. Similar to Chetty et al. (2014), I find that there is a higher elasticity in the South and lower persistence across generations in the states at the West Coast and in the Midwest. One notable exception is Wyoming, which could be due to a low number of observations in this state (84 in total). The only state with not enough observations is Montana (shown in white). The map shows that even with a much smaller data set, the regional distribution of social mobility is similar to the map constructed with administrative data, though it lacks geographic granularity. The estimates used for the construction of the map do not account for demographic characteristics in order to establish comparability with the maps of Chetty et al. (2014) as the authors do not have these information, hence their maps only rely on rank-rank correlations.

Figure 2.2: Intergenerational Mobility by State



(a) Intergenerational Elasticity (b) Labor Market Polarization

Notes: The left panel shows map shows the spatial distribution of the point estimates of intergenerational elasticity for all states adjusted for changes in inequality over time. Darker colors indicate higher point estimates, i.e. states with higher immobility. The spatial distribution is similar to that of the commuting-zones in Chetty et al. (2014)[Fig. VI]. The Southeast is on average much more immobile than other regions in the United States. The right panel shows the rise of non-college service employment between 1990 and 2010 as a proxy for labor market polarization.

Panel (b) in the same figure shows the degree of labor market polarization proxied by the rise in non-college service employment between 1990 and 2010. The two maps show strong spatial correlation between labor market polarization and intergenerational elasticity. As argued above for the model, intergenerational elasticity for the two "extreme" skills, i.e. manual and abstract, should go up with labor market polarization, whereas IGE should decrease for children whose parents work in routine occupations. The overlap of the maps seems to indicate that the tails of the occupational groups dominate the middle.

2.4 Empirical Evidence

In this section I confront the key model predictions with the data. First, I provide empirical evidence that labor market polarization reduces intergenerational mobility across space and time. For the former, I exploit data on absolute upward mobility from Chetty et al. (2014), who compute the expected rank of children in the national income distribution from parents who are located at the 25^{th} percentile of the national income distribution. For the development across time, I make use of the PSID data and determine whether intergenerational elasticity changes over time for children where the heads are working in manual, routine or abstract occupations.

The main channel proposed in the model is educational choice. The model predicts that educational attainment of young labor market entrants becomes more polarized as wages for routine occupations decline. I start by showing that education became more polarized in the United States between 1970 and 2018 using Census data among the group of young people between 20 and 29 and in the labor force. I also compute "family premia" for various educational levels depending on the educational level of parents. The next step encompasses to estimate the impact of changes of the decline in routine employment educational polarization. The last part of education exploits the Educational Supplement from the Current Population Survey, and allows me to investigate how educational choice depends on the interaction of past labor market polarization and family background.

In order to lend further support to the model, I conclude the empirical analysis with evidence that the "qualifying predictions" from the model in Section 2.2 hold in the data. Specifically, I focus on density, ICT investment, and housing prices.

2.4.1 Upward Mobility

In this section I estimate the causal impact of labor market polarization on intergenerational mobility exploiting geographic variation in the expected rank of children from low-income income families. Chetty et al. (2014) provide the data for the birth cohorts from 1980 to 1982. This means that they enter the labor market around the year 2000. The authors measure the income rank of these birth cohorts around the age of 30. I proxy labor market polarization as the decline in routine employment relative to working-age population on the commuting-zone level. This implies that a *higher value* of the proxy implies *weaker* labor market polarization.

2.4.1.1 Empirical Specification

Endogeneity concerns can arise for two reasons. First, omitted variables bias can distort the point estimates. A region's capacity or willingness to absorb new ideas and technology independent of the background of the inventors might be correlated with both labor market polarization and intergenerational mobility. A higher degree of absorption may increase polarization because new ideas typically spread first within the same region. Aghion et al. (2018) shows that innovation by new entrants relates positively with upward mobility. The positive correlation between both the dependent and independent variable introduces a downward bias.[11] The second bias can arise from measurement error. It is crucial to remember that data on upward mobility provided by Chetty et al. (2014) are

[11] Normally, a positive correlation of the omitted variable with both the dependent and independent variable causes an upward bias. But as I proxy labor market polarization with a change in routine employment, and a higher value implies lower polarization, a downward bias is the consequence.

point estimates with a standard error, i.e. the measures are not actually observed, but inferred from administrative records. This introduces some potential measurement error, implying a bias towards zero if the error is random.

To encounter the endogeneity concerns, I estimate the causal impact of labor market polarization on upward mobility using an instrumental variable (IV) estimation strategy. The instrumental variables I use to estimate the causal impact of labor market polarization on the intergenerational mobility builds on the model in Section 2.2. Specifically, I use both (log) density of a commuting-zone and the share of routine-intensive employment in 1970.[12] I exploit variation in 1970 as the arrival of the first three commercially successful computers occurred in 1977, the so-called "1977 Trinity". Based on the model, an alternative to log density as instrumental variable is total population. However, density seems a more appropriate measure compared to population as interactiveness and proximity for both manual and abstract tasks have been highlighted in the literature.

In order to identify the causal impact with an IV estimation, two conditions have to be met. First, the instrument must induce a change in the endogenous variable as theory predicts. Based on previous findings and the model outlined above, this means that historical routine task-intensive employment and log density must have a negative impact on the change in routine employment in the first stage. The second condition of a valid IV is the exclusion restriction, in particular the instruments are not allowed to have an effect on upward mobility other than through its effect on polarization conditional on covariates.

The identification strategy to estimate the causal impact of labor market polarization on upward mobility takes on the following form:

$$IGM_{js} = \beta_0 + \beta_1 \Delta Routine_{js} + \boldsymbol{X}'_{j2000}\Theta + \gamma_s + \varepsilon_{js}, \tag{2.18}$$

$$\Delta Routine_{js} = \alpha_0 + \alpha_1 log(Density)_{j1970} + \alpha_2 RoutineShare_{j1970} + \boldsymbol{X}'_{j2000}\Theta + \gamma_s + e_{cs} \tag{2.19}$$

where IGM_{js} denotes the expected rank of children in the national income distribution from parents from the 25th percentile in commuting zone j in state s. $\Delta Routine_{js}$ is the change in routine employment between 1990 and 2010 because the income rank of the baseline cohorts from Chetty et al. (2014) is measured between 2011 and 2012. The vector of controls $\boldsymbol{X}'_{j2000}$ contains covariates from the main specification in Autor and Dorn (2013, Table 5) from the year 2000 in order to account for labor market conditions when the baseline cohorts in the data on upward mobility by Chetty et al. (2014) enter the labor market. It includes various demand and supply shifters, specifically the ratio of college to non-college educated individuals in the population, the unemployment rate, the share of employment in manufacturing, the elderly share of population, the female

[12] I show below that historical log density is a good predictor for ICT investment per worker and that the relationship is increasing over time.

labor force participation rate and the start-of-decade fraction of non-college workers in a commuting zone whose real wage is below the minimum wage that will be enacted in the subsequent decade.[13] The regression also includes state-dummies (γ_s). Observations are weighted by the commuting zone share of national population in 1980. Standard errors are robust to heteroscedasticity.

The parameter of interest is β in equation (2.18), which exhibits a *positive* sign if labor market polarization has a detrimental impact on absolute upward mobility. Potentially, the impact could be positive due to upward mobility if children from low-income parents leap over the middle of the income distribution and enter abstract high-paying occupations. In the model, this does not occur at a higher rate with ongoing labor market polarization because I assume symmetry for manual and abstract occupations. However, as Autor and Dorn (2013) show, the wage increase for high-skilled workers is larger than for low-skilled workers. Equation (2.19) shows that labor market polarization is regressed on the instrument, namely log density and the share of routine employment in 1970. The important parameters in the first stage represented in the equation are α_1 and α_2. Based on the model and findings by both Davis et al. (2020) and Eeckhout et al. (2014), the first parameter should be negative for the change in routine occupations. The sign should be equivalent for the historical share in routine-intensive occupations based on Autor and Dorn (2013).

2.4.1.2 Results

Table 2.3 provides evidence that labor market polarization reduces absolute upward mobility. The first two columns present the results for the ordinary least square (OLS) estimator. The first column does not include any controls nor state-fixed effects, whereas the latter one includes both. Column (3) displays the causal effect of labor market polarization on upward mobility based on the IV identification strategy with historical log density and historical routine employment as instrumental variables. The lower panel shows the first stage results. Overall, the results suggest a negative relationship between intergenerational mobility and labor market polarization. A less strong decline in routine employment, i.e. weak labor market polarization, increases the expected ranks of children of parents at the 25$^{\text{th}}$ percentile of the income distribution. This relationship is both economically and statistically meaningful. As argued above, the point estimates are likely biased towards zero, which is reflected in the difference between the OLS and IV estimates.

The point estimate in column (3) of the first panel indicates that an increase of one percentage point in labor market polarization leads to a decline of .57 expected ranks of a

[13] I exclude the share of the non-college population that is foreign born because upward mobility is substantially higher for migrants (see e.g. Abramitzky et al. (2019)).

child whose parents are located at the 25th percentile of the income distribution. This result is economically meaningful as the median commuting zone lost 7.70 percent of routine jobs relative to the working-age population. Extrapolating out of sample therefore implies that a child moving from the median commuting-zone in terms of routine employment decline to a commuting zone without labor market polarization is expected to be located 4.4 ranks higher in the national income distribution. According to Chetty and Hendren (2018b), a one percentile increase corresponds to a higher income of approximately 818 USD. Taking the average income of children with parents earning below median from the same authors, i.e. 26,091 USD, a move as described before translates into 13.79% higher income.

Table 2.3: Effect of labor market polarization on upward mobility

I. 2nd Stage	(1)	(2)	(3)
	OLS	OLS	IV
Δ Routine Emp.	0.77***	0.23***	0.57***
	(10.63)	(4.41)	(5.38)
State FE	No	Yes	Yes
Controls	No	Yes	Yes
Obs.	693	693	693
R^2	0.26	0.75	
F-Statistic			122.32
II. 1st Stage			
Log Density (1970)			-0.40***
			(-4.36)
Routine Emp. (1970)			-0.24***
			(-12.29)
Partial R^2			

Notes: The dependent variable of the second stage of the IV approach is absolute upward mobility regressed on labor market polarization measured as the change in routine employment between 1990 and 2010. The lower panel shows the first-stage results. Control variables and state fixed effects are not shown. Observations are weighted by population share in 1980. t-statistics are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

The second panel of the same table shows the estimation results of the first-stage, i.e. equation (2.19). Based on the model, (log) density should impact the decline in routine occupations and the rise in manual workers negatively and positively, respectively. The underlying idea is that the more dense region is demanding more capital, hence leading to stronger automation of routine tasks and, consequently, experience stronger labor market polarization. The results suggest that the prediction from the model holds true, an increase of population density by 1 percent is associated with an decrease of routine employment by .40 percentage points. Unsurprisingly, historical specialization in routine employment exhibits the same sign. In line with expectations and the authors findings, this point estimate is also positive and at a similar scale in the OLS estimations in Autor and Dorn (2013, Table 5, Panel A). All point estimates are statistically significant at all conventional levels and the F-Statistics is far above the value of 10.

Table 2.4 extends the benchmark analysis by introducing further control variables, which are associated with upward mobility. Based on previous research, Chetty et al. (2014) sort them into nine different categories plus the fraction of black residents. Because all nine categories encompass three covariates, I exploit the first principal component of each category. The original data is taken from Chetty et al. (2014) and usually measures the variables around the year 2000, i.e. when the benchmark cohorts enter the labor market. This coincides with the timing of labor market controls included in vector $\boldsymbol{X}'_{j2000}$ in the baseline regressions.

First, migration (MIG) encompasses the fraction of foreign born and both migration inflows and outflows. Second, labor market conditions (LAB) contain the share of manufacturing, Chinese import growth and the teenage labor force participation rate. Third, college education (COL) measures colleges per capita, college tuition and college graduation rate. Fourth, local tax policies (TAX) includes local tax rates, state EITC exposure and tax progressivity. Fifth, family structure (FAM) involves the fraction of single mothers, the divorce rate and fraction married. Sixth, social capital (SOC) comprises a social capital index, fraction religious and the violent crime rate. Seventh, high-school education (K12) consists of student-teacher ratio, test scores and drop-out rate. Eighth, income distribution (INC) includes mean household income, the Gini coefficient and top 1% income share. Ninth, segregation (SEG) contains an index of racial segregation, segregation of poverty and the fraction commuting less than 15 minutes to work. Lastly, I add the fraction of black residents (BLA). Most variables in the first four categories exhibit weak correlations with absolute upward mobility, while the correlations are stronger for the variables in the last five categories.

Table 2.4 shows that the overall negative relationship between labor market polarization and upward mobility holds. As before, the sign of the coefficients is positive as I use the change in routine employment between 1990 and 2010 as a measure for labor market polarization. In most estimations, the coefficient for labor market polarization is largely unchanged compared to the point estimate of the IV point estimate in Table 2.3. Disregarding the specification with segregation (by income and race) in column (9) the point estimates range between .24 and .62. In all these specifications, the coefficient of labor market polarization is still statistically significant at the 1% level. The addition of the various covariates without a strong decline in the point estimate of labor market polarization indicates that labor markets play an important role for intergenerational mobility as suggested by Rothstein (2019).

Columns (3) and (7) in Table 2.4 include the first principal components of the covariates describing the education system, i.e. college and high-school education, respectively. Especially the specification including the principal component for high-school education exhibits a substantial decrease. This is indicative of the importance of the education sys-

Table 2.4: Effect of labor market polarization on upward mobility - Additional Controls

I. 2nd Stage	(1) MIG	(2) LAB	(3) COL	(4) TAX	(5) FAM	(6) SOC	(7) K12	(8) INC	(9) SEG	(10) BLA
Δ Routine Emp.	0.92***	0.81***	0.75***	0.82***	0.41***	0.78***	0.58***	0.72***	0.06	0.67***
	(6.11)	(5.74)	(5.77)	(6.12)	(3.77)	(6.18)	(3.64)	(5.00)	(0.52)	(5.40)
Obs.	691	693	563	693	693	666	663	693	693	693
F-Statistic	69.88	84.37	77.46	83.18	55.33	67.08	69.30	60.59	36.15	72.65
II. 1st Stage										
Log Density (1970)	-0.36***	-0.41***	-0.39***	-0.39***	-0.34**	-0.34***	-0.23*	-0.03	-0.26	-0.30**
	(-3.01)	(-3.41)	(-2.90)	(-3.24)	(-2.58)	(-2.70)	(-1.82)	(-0.22)	(-1.56)	(-2.22)
Routine Emp. (1970)	-0.25***	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***	-0.23***	-0.23***	-0.23***	-0.25***
	(-9.09)	(-9.73)	(-9.17)	(-9.32)	(-9.61)	(-9.36)	(-8.74)	(-9.75)	(-8.90)	(-9.75)
R^2	0.72	0.72	0.72	0.72	0.72	0.72	0.74	0.73	0.72	0.72

Notes: The dependent variable of the second stage of the 2SLS approach is absolute upward mobility regressed on labor market polarization measured as share of non-college service employment. Columns (1) to (9) include the first principal component of all variables included in Chetty et al. (2014, Figure 8). MIG stands for migration, LAB for labor markets, COL for college, TAX for the tax system, FAM for family, SOC for social capital K12 for high-school, INC for properties of the income distribution, SEG for segregation, and BLA the fraction of black residents. Control variables and state fixed effects are not shown. Observations are weighted by population share in 1980. t-statistics are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

tem on upward mobility. The point estimates in columns (5) and (10) are also substantially smaller than the benchmark point estimate. They include family characteristics and the share of blacks, respectively. While the former exhibits strong negative correlations with upward mobility, this is likely driven by design. This is because Chetty et al. (2014) measure income on the family level, and therefore the share of single mothers is strongly negatively related to upward mobility. The result in column (5) is entirely driven by the share of single mothers.[14] However, Chetty and Hendren (2018b) show that the causal impact of family structure is small. With respect to the share of blacks, this result is potentially driven by lower levels of upward mobility for blacks compared to other races as shown by Chetty et al. (2020).

The main exception is SEG in column (9), where the point estimate of labor market polarization is not statistically significant and actually changes signs. The results does not seem to be driven by a specific variable included in the first principal component. The F-Statistic is also the lowest for this specification, though it is still comfortably above the critical value of 10, one explanation could be that segregation of poverty and/or race is stronger in dense areas. Boustan (2013) argues that educational attainment and earnings are lower for blacks in more segregated cities, while Quillian (2014) generalizes these findings for advantaged versus disadvantaged groups. Consequently, segregation potentially plays a crucial role for upward mobility as argued by Fogli and Guerrieri (2019).

In most specifications, the first-stage results are similar to the benchmark results, i.e. the coefficient for log density is typically larger than the point estimate for historical routine employment. Exceptions are INC and SEG, where the point estimate for log density is statistically insignificant, and close to zero for the former. This is unsurprising, however, as for example in more dense regions average income is higher, as is also predicted by the model in Section 2.2. Somewhat more surprising is that segregation seems to be an issue in more dense commuting-zones. The coefficient for specialization in routine employment stays also similar to its value in the benchmark specifications, but stays statistically significant in all specifications.

2.4.2 Intergenerational Elasticity

After determining whether the empirical evidence supports the key prediction that labor market polarization reduces upward mobility across space, I now turn to variation across time. Due to data constraints on absolute upward mobility over time, I exploit a different measure of intergenerational mobility, namely intergenerational elasticity (IGE). It is defined how strong parental income affects the children's income during adulthood.

The model predicts divergent patterns of intergenerational elasticity depending on

[14] The point estimate for $\Delta Routine$ when excluding the share of single mothers when constructing the principal component for FAM is .60, and not significantly different from the benchmark point estimate in Table 2.3.

parental background. Specifically, with progressing labor market polarization IGE should be higher for children with parents in manual and abstract occupations. This is driven by both less transitions from each of these groups into routine occupations and higher persistence to choose the same educational attainment as their parents. On the other hand, IGE should fall for children from parents in routine jobs as the rate of transitions increases into both directions, rendering parental income less important than for the other two groups. This measure allows me to investigate trends over time, and to investigate patterns of intergenerational mobility across various parental backgrounds. Precisely, I define the occupation of the household head during teenagehood as the parental background.

2.4.2.1 Empirical Strategy

Using the PSID data described in Section 2.3, I estimate the intergenerational elasticity for each group dependent on parental background. The drawback of using the occupation of the household head when the individual was a teenager is that I cannot measure whether the parent actually lost their job due to labor market polarization. Instead, the occupational status of the head serves as indicator of exposure to rising automation of routine tasks. In the baseline estimation, I differentiate between manual, routine and abstract occupations. I follow the standard literature in terms of estimation strategy by accounting for the life-cycle bias of both parents and children. Adopting this strategy from Lee and Solon (2009) allows me to exploit the entire pool of available data, i.e. pairwise children and parents. The estimation equation takes on the following form:

$$ln\, y_{c_{it}} = \beta_0 + \beta_1 ln\, y_{p_i} + \beta_2 [ln\, y_{p_i}] OccHead_i + X_i' \Omega + \sum_{n=1}^{4} \delta_n A_i^n + \sum_{n=1}^{4} \gamma_n C_{it}^n + \sum_{n=1}^{4} \theta_n [ln\, y_{p_i}] C_{it}^n + \varepsilon_{it}, \tag{2.20}$$

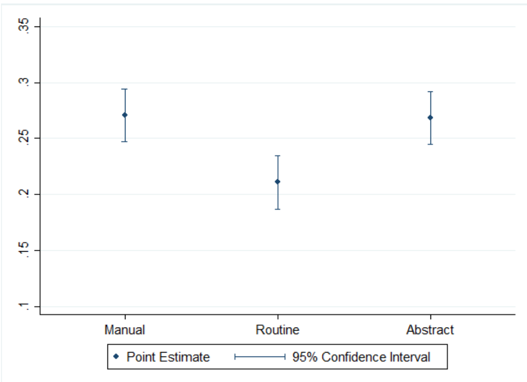
where $y_{c_{it}}$ measures the real family income (in logs) of adult children from family i in year t. Similarly, y_{p_i} represents average real family income (in logs) when the child was between 13 and 19. The vector X' includes demographic variables such as education, race, marital status and a binary variable indicating whether the individual is a head or a spouse, and the occupation of the head during teenagehood. To account for the life-cycle bias of the parents, A_i, and parameters δ_1 to δ_4, depict the age of the head in family i when the child was 16 years old. Equally important is to account for the life-cycle bias of children, I control for the fourth polynomial of child's age centered around the age of 40, represented by C_{it} and parameters γ_1 to γ_4. This is in line with Black and Devereux (2011) who show that income around the incomes around the middle of the life-cycle is the best proxy of permanent income. The polynomial of child's age (centered around 40) is also interacted with parental income during teenagehood in order to account for potential divergence in income patterns across the life-cycle depending on parental income.

The main interest lies in the linear combinations of the estimated coefficients β_1 and the vector β_2. As the modifying variable $OccHead_i$ is a categorical variable, I can simply sum up the coefficients of interest as laid out in Brambor et al. (2006), and in order to compute meaningful standard errors I use the equations by Aiken et al. (1991). To get consistent estimates across time, I harmonize occupation data in the PSID with the help of IPUMS crosswalks as the PSID uses of occupational codes from the Decennial Censuses.

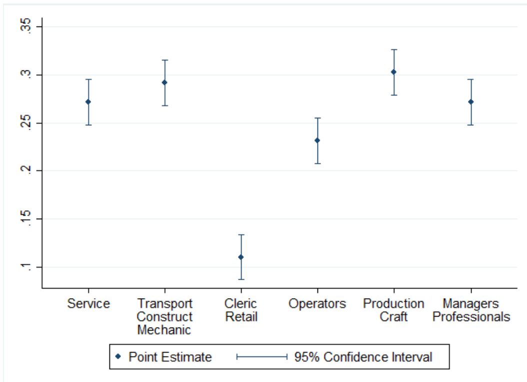
2.4.2.2 Results

Figure 2.3 presents how intergenerational elasticity differs depending on occupational background of the head. The left panel differentiates occupations by three groups, namely manual, routine and abstract. This is equivalent to the task framework by Autor et al. (2003), and the right panel broadens the number of occupational groups to six, following Autor and Dorn (2013, Table 2). I have sorted the six groups along the more coarse three occupational groups according to the findings of the authors. The first two of the six groups are manual occupations, while the next three groups are more routine-intensive. Finally, the last subgroup is analogous to the group of abstract occupations.

Figure 2.3: IGE by Occupational Background



(a) Three Categories



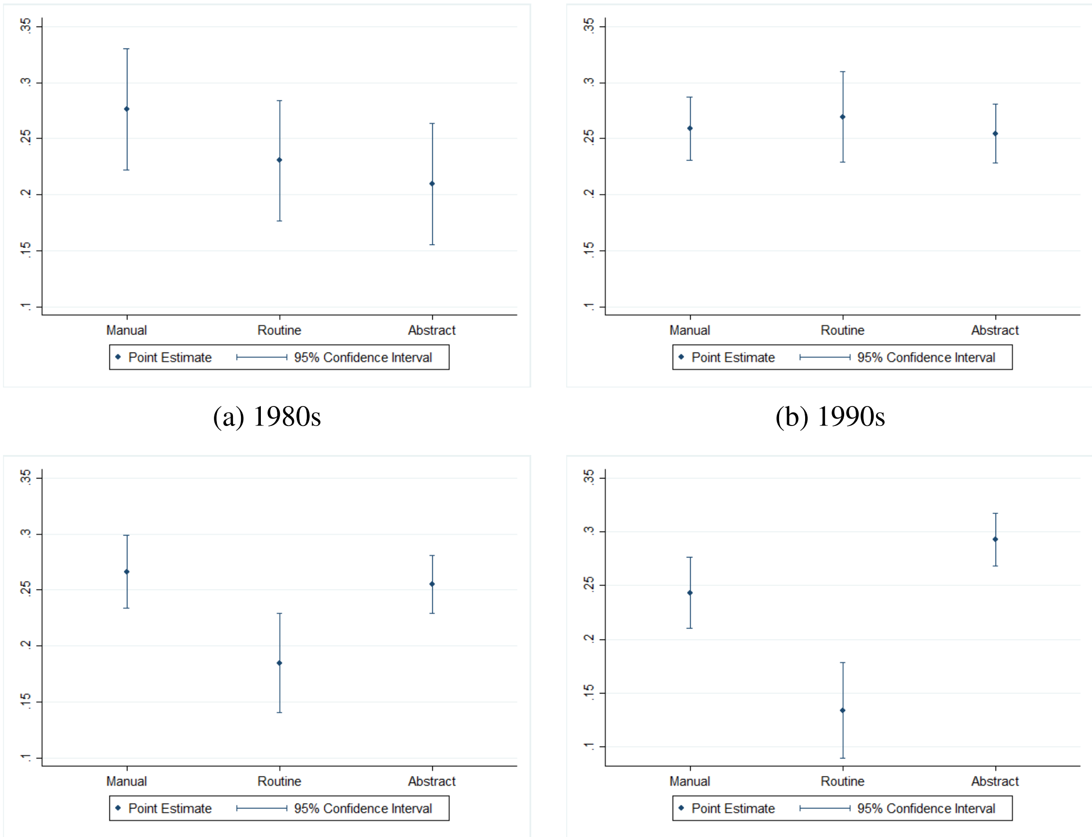
(b) Six Categories

Notes: The left panel shows the point estimates of intergenerational elasticity (IGE) based on the three occupational categories referred to in the task framework in Autor et al. (2003), i.e. manual, routine and abstract. A u-shaped pattern is visible, indicating that parental income is more important for the child's income if they are coming from the lower or upper part of the occupational structure. The right panel breaks up these three broad categories into six categories. The first two categories belong to manual occupations, the following three belong to routine occupations, and the last coincides with abstract occupations.

Both panels of Figure 2.3 exhibit a u-shaped pattern of intergenerational elasticity depending on occupational background. This provides evidence that parents influence their children's income stronger if they work in a manual or an abstract job, compared to parents who work in routine employment. IGE is essentially equal for children with parents working in manual and abstract occupations with a value slightly above .27. IGE is lower for children with parents working in routine-intensive occupations with a value of $\approx .22$.

The 95% confidence intervals indicate that the point estimates for manual and abstract are statistically different from routine. The point estimates are quite low compared to previous studies because I include a wide range of demographic characteristics as covariates.
The right panel with the slightly more granular division of occupational groups gives some more insights, specifically whether any particular subgroup drives the results. Interestingly, the intergenerational elasticities if parents work in any subgroup within manual occupations, i.e. service or transport/construction/mechanic, are statistically not different from one another. The low level of IGE within the group of routine occupations is particularly driven by the occupation group of clerics and retailers, a group strongly associated with routinization and labor market polarization. The point estimate is below .15. On the other hand, children whose parents work in production or craft, which is the highest paying routine occupation, the IGE slightly surpasses that of abstract occupations, albeit they are not statistically different from one another. Obviously, the point estimate and the standard errors for the final more granular subgroup are equivalent to that of abstract ($\approx .27$) in the left panel as the group of abstract occupations is not divided into multiple groups.
Besides the investigation of various family backgrounds, the PSID also allows me to extend the baseline estimation to examine whether the levels of intergenerational elasticity have changed over time. I estimate equation (2.20) where I extend the modifying variable, i.e. $OccHead$, to the interaction between occupational group and decade, and include decade-fixed effects. The triple interaction consisting of parental income during teenagehood, occupational category and decade works similar to before. In other words, I am interested in the linear combination of the coefficients of the various interaction terms and the triple interaction. The calculation of the point estimates works similar to before, and for meaningful standard errors I now apply the formula for triple interactions by Aiken et al. (1991). Based on the model prediction in Proposition 1 is correct, then the u-shaped pattern of intergenerational elasticity across occupational backgrounds should either evolve or become stronger over time.
Figure 2.4 shows the same coefficient plots as the left panel in Figure 2.3 for the all decades since the 1980s. Panel (a) shows IGE by parental occupation during the 1980s, where a declining pattern across occupational group is recognizable, however there is no statistically significant difference between any pair of point estimates. During the 1990s, there is no sizeable nor statistical difference between all three groups in terms of the intergenerational mobility. In the 2000s, i.e. after the preceding boom in computer capital investment, the u-shaped pattern starts to emerge. Finally, in the 2010s when labor market polarization has progressed the most within the sample period, there is a clear u-shaped pattern across occupational groups. In the 2010s the point estimate of the IGE for children whose parents work in abstract occupations is even higher than for those children whose parents work in manual employment.

Figure 2.4: IGE by Occupational Background and Decade



(a) 1980s (b) 1990s

(c) 2000s (d) 2010s

Notes: The four panels repeat the same analysis of intergenerational elasticity by parental occupation as in the left panel of Figure 2.3, but differentiates by decade. This allows for an analysis how IGE changed over time. It shows that the u-shaped pattern seen above occurs over time, in particular between the 1990s and 2000s, and is reinforced in the 2010s.

Overall, the strongest movements in intergenerational elasticity over time occur for children with parents working in either routine or abstract occupations. In particular, Figure 2.4 shows that the importance of parental income decreases the strongest over time for children with a routine background, whereas it increases significantly for children with an abstract background. The point estimate for the former falls from around .27 in the 1990s to below .15 in the 2010s, while the latter increases from .21 in the 1980s to close to .30 in the 2010s. On the other hand, the point estimate of intergenerational elasticity for children with parents working in manual employment stays largely constant with a value of .27. Only in the 2010s, there is a slight decrease to around .25, but the point estimate is not statistically significant from the previous decades.

2.4.2.3 Transition Matrices

Table 2.5 presents descriptive evidence for the transition between occupational groups and how it changes over time. Given that the price of capital fell over time in the last decades,

Table 2.5: Transition Matrices between 1980 and 2017

(a) 1980s

	Child Occupation		
	Manual	Routine	Abstract
Parental Occupation	%	%	%
Manual	41.5	29.5	29.0
Routine	28.8	36.7	34.4
Abstract	24.0	24.7	51.3

(b) 1990s

	Child Occupation		
	Manual	Routine	Abstract
Parental Occupation	%	%	%
Manual	43.5	26.7	29.8
Routine	35.4	34.0	30.6
Abstract	21.5	22.9	55.6

(c) 2000s

	Child Occupation		
	Manual	Routine	Abstract
Parental Occupation	%	%	%
Manual	51.3	21.1	27.6
Routine	33.9	25.3	40.7
Abstract	25.8	22.6	51.7

(d) 2010s

	Child Occupation		
	Manual	Routine	Abstract
Parental Occupation	%	%	%
Manual	48.1	22.1	29.9
Routine	39.2	22.8	38.0
Abstract	27.7	19.5	52.8

Notes: The tables show the transition matrices between the three major occupational categories between parents and children. They show transition probabilities over time, that is by decade. On the left axis, the table lists the parental occupations, while it lists the same occupational groups for children at the horizontal axis.

which lead to an automation of routine occupations, the model predicts rising transitions from routine to both manual and abstract, and less transitions vice versa. Starting with Table 2.5a, which shows transitions between parental and child occupation between the three occupational groups of interest during the 1980s, it is evident that the majority of children is working in the same occupational group as their parents. This observation is not surprising given the evidence of strong intergenerational transmission of occupations between parents and children, shown, among others, by Hellerstein and Morrill (2011) and Ferrie (2005) for the United States. Over time, the "immobility" across occupational groups becomes stronger for both manual and abstract levels, whereas it falls for the case where parents work in routine occupations. Instead, the probability to transition into either manual or abstract work is already higher than to stay in a routine occupation in the 2000s (see Table 2.5c).

2.4.3 Polarization of Educational Attainment

Educational choice is the mechanism how labor market polarization detrimentally affects upward mobility of children from low-income parents. The model predicts that falling prices for capital reduce the returns to secondary education, and therefore individuals are increasingly choose more extreme levels of education, i.e. primary or tertiary education. This section provides evidence that education has become more polarized in the United States over time, and that the increase in educational polarization is linked to local patterns in labor market polarization.

In order to quantify the impact of education, I estimate the previous model in equation (2.18 including covariates for both college and high-school education. Second, I estimate equation 2.20 excluding educational attainment in the vector of demographic characteristics. I compare the point estimates, where the differences between the respective coefficients allow me to quantify the impact of education on upward mobility. When including the principal components for both COL and K12 in the estimation of upward mobility, I obtain a point estimate of .38. Compared to the baseline estimate of .57, it falls by around 33%. The coefficients for intergenerational elasticity of income for all three categories are substantially higher. For parents working in manual, routine and abstract occupations, they are .387, .281 and .416, respectively. Compared to the point estimates including the individual level of education, the point estimates fall between 25 and 36 percent. Both these exercises provide evidence that the education accounts for at least 30 percent of intergenerational mobility.

I illustrate rising polarization in educational attainment in four stages. First, I calculate polarization indices for educational attainment of young labor market entrants for the United States as a whole. Second, I compute family premia based on Checchi et al. (2013) using the PSID. This allows me to compute how the probability of achieving a specific level of educational attainment depends on parental education for birth cohorts from 1955 until 1990. Third, I relate educational polarization with decadal changes in routine employment exploiting variation across time and commuting zones. Last, I focus on individual education decisions using data from the educational supplement of the Current Population Survey, and how they depend on both past regional polarization and family background.

2.4.3.1 National Educational Polarization

The model predicts an adjustment of labor supply with respect to education over generations as routine wages are declining. To see whether this holds true, I compute polarization indices for educational attainment using the Decennial Census for the years 1970 to 2000 and the American Community Service 2010 and 2018. I focus on respondents between the age of 20 and 29 as they have entered the labor market recently and respond the strongest to labor demand. Adão et al. (2020) provide evidence that changes in skill demand for cognitive skills have affected younger workers more than older workers. Further, I limit the sample to the labor force, i.e. I only exploit education decisions of employed or unemployed, and not individuals still in education or outside of the labor force for other reasons. Finally, I have excluded observations with zero or non-available schooling.[15]

Importantly, educational attainment is measures as a categorical variable in the Decennial Censuses and the ACS. Therefore, standard measures of spread or tailedness like standard deviation and kurtosis obsolete because they employ the mean as a center in the space of the distribution. The same holds for the polarization index by Esteban and Ray (1994) as they consider the mean as the central point. Allison and Foster (2004) prove that the mean is not a suitable central point to measure polarization for categorical variables. Instead, the authors argue that median should serve as the central point of the distribution. However, one issue with all measures which compute the polarization of distributions with ordinal data is that they require the same median in order to compare the polarization index.

Educational attainment is measured in eleven categories, and the values six and ten indicate high-school graduation and four years of college, respectively. All polarization indices are equal to zero if all individuals acquire the same level of education, i.e. when every labor market entrant has the same educational attainment equivalent to the median. The indices can rise for two reasons: first, the larger the share of young labor market entrants who do not acquire the same level as the median individual, and second, the further away the same share of individuals are from the median individual. In the case of education, the indices would reach their maximum if 50% of the individuals achieved the lowest level of educational attainment (grade 4) and the other 50% achieved the highest level of educational attainment (5+ years of college), with the median individual obtaining a high-school degree.

I compute various polarization indices for education. The first measure is based on Allison and Foster (2004), subsequently abbreviated "AF". Its main drawback is its scale dependence. In other words, the maximum value of the AF index depends on the range of categories of the distribution. The second polarization index is based on Naga and Yalcin (2008), abbreviated by "ANY" in the subsequent tables. It has two advantages compared to the AF index. First, it is not scale dependent, instead it ranges between zero and one. Second, it allows me to put different weights on the mass below or above the median. This feature allows me to determine whether only one side of the distribution is affecting the overall index of educational polarization. Especially with respect to education and the upskilling over the last decades this feature provides useful insights. The index relies on two parameters, expressed as ANY(α, β). A higher value of α indicates that more weight is put on the upper part of the distribution, i.e. above the median. Conversely, a higher

[15] In the Census files, the same value represents both possibilities. As it seems more likely to have no data on education than to observe individuals without any schooling, I decide to exclude these observations.

value of β indicates that more weight is put on the lower part of the distribution, i.e. below the median. This means that I can determine with this index whether polarization is driven by movements above or below the median, or both. The baseline measure of ANY(1,1) is equal to AF divided by the number of categories.

Table 2.6 shows the development of educational polarization in the United States. Columns (1) and (2) indicate the census year used for the computation and which cohorts are included in the sample due to the restrictions explained above. Column (3) shows the median because all measures are median-preserving, i.e. the polarization over different distributions can only be compared if the median coincides between different distributions. The median labor market entrant from the cohorts 1941 to 1960 has a high-school degree. This changes for all subsequent cohorts, where the median individual acquires a level of education equivalent to one year of college. This allows me to compare young labor market entrants who were particularly affected by the rise of ICT capital.

Table 2.6: Educational Polarization

(1) Year	(2) Cohorts	(3) Median	(4) AF	(5) ANY (2,1)	(6) ANY (1,2)	(7) ANY (4,1)	(8) ANY (1,4)
1970	1941-50	6	3.15	.30	.37	.37	.47
1980	1951-60	6	3.11	.34	.38	.44	.47
1990	1961-70	7	2.72	.26	.31	.30	.39
2000	1971-80	7	2.99	.29	.35	.34	.43
2010	1981-90	7	2.96	.30	.35	.37	.43
2018	1989-98	7	3.01	.34	.37	.44	.45

Notes: This table shows various measures of educational polarization for young labor market entrants between the census years 1970 and 2018. It is important to keep in mind that all polarization indices are only comparable if the median in Column (3) is the same. Column (4) shows the Allison and Foster (2004) polarization measure (AF) and ANY(α, β) in Columns (5) to (8) measure polarization based on Naga and Yalcin (2008) with varying parameter values to put more weight on different parts of the distribution. Columns (5) and (7) put more weight on the upper part of the distribution, and columns (6) and (8) put more weight on the lower part of the distribution of educational attainment.

Columns (4) to (8) present the different indices of the educational polarization for labor market entrants between 20 to 29. The table shows a strong increase in the AF indicated by Column (4) between 1990 and 2000, i.e. during the time of the boom in computer capital. This view is confirmed by the ANY indices with varying parameters. Independent on whether I stress the upper part - reflected in Columns (5) and (7) by the higher value of α - or the lower part - reflected in Columns (6) and (8) by the higher value of β - of the distribution, there is a substantial increase during the same period. Specifically, the rise in all ANY(α, β) indices, is about 10% over this period, which is equivalent to the overall change in AF in Column (4). After this strong rise, the polarization indices continue to increase slightly, but at a slower rate. The upper part of the education distribution constitutes an exception as indicated by Columns(5) and (7), it sees a strong rise between 2010 and 2018 as well.

Educational attainment of young labor force participants has become more polarized in the United States between 1990 and 2018. However, the polarization do not allow me to investigate whether individuals make extreme education choice influenced by labor market polarization nor family background.

2.4.3.2 Family Premia

The main advantage of the Panel Study of Income Dynamics is that I can investigate educational choices by parental background. It is crucial to clearly identify the impact of parents on educational choices of young labor market entrants. The standard approach typically estimates intergenerational transmission of education the following way:

$$c_i = \alpha + \rho f_i + \varepsilon_i,$$

where c_i and f_i are the number of years of education of child and father, respectively, from family i, each normalized by their respective standard deviation. The decomposition of ρ by Checchi et al. (2013) shows that the coefficient also reflects the general upskilling of the population during the second half of the last century. Based on the decomposition, the authors propose multiple indicators of intergenerational persistence of education. I focus on the "family premium" for a given education level, which indicates whether a child experiences a benefit or a penalty of achieving the education level. Formally, it is defined as:

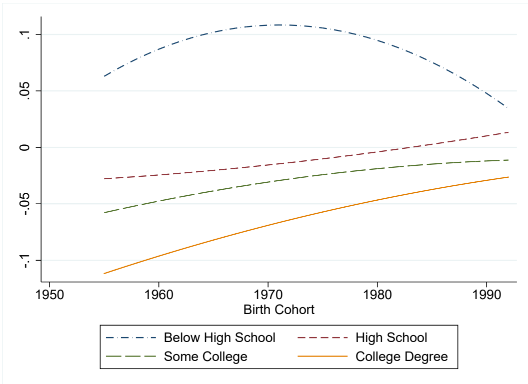
$$Pr(c = t | f = j) - Pr(c = t), \tag{2.21}$$

where t, j are specifying different education levels, which may coincide or not. I choose four levels, namely high school dropouts, high school graduates, some college and college degree.

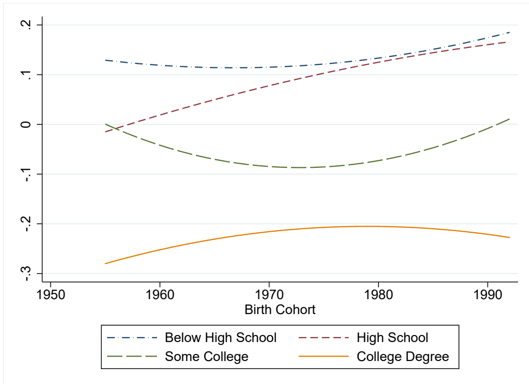
Figure 2.5 show the results for the different family premia for a given education level t by background j. Panel (a) shows the family premia for dropping out of high school, for which all family premia are mainly rising, only for children whose parents also have less than high school education, the family premia premium is falling since the 1970 cohort. Panel (b) depicts the evolution of the family premia for high school graduation for all backgrounds. Interestingly, the family premia are rising for all backgrounds, albeit it rises the strongest for children whose parents are also high school graduates. The family premia for high school graduation for children whose parents have either some college or a college degree behave somewhat differently over time. The former first falls over time until the mid-1970s cohorts, and then rises again steeply, with a similar family premium for the 1955 and 1991 cohorts. The family premium where parents have a college degree rises until the 1980s cohort and then slightly declines.

Focusing on the two lower panels in Figure 2.5, the family premia for children whose parents are either high school or college graduates is falling over time. Treating "some college" as the category suitable for routine occupations, then the empirical evidence in panel (c) is largely in line with the model predictions: less children whose parents have "extreme" educational backgrounds tend to enter less the middle category of "some college". On the other hand, the family premium is slightly rising, but is plateauing since the early 1970s cohort. The model would have predicted a decline for this development as well, but the family premium has to be considered in comparison to other backgrounds. One strong exception is the spectacular rise of the family premium for "some college" for children whose parents do not graduate high school. It is growing over time for all birth cohorts under consideration, and starts out with the lowest value, and in most of the 1980s it is already the highest.

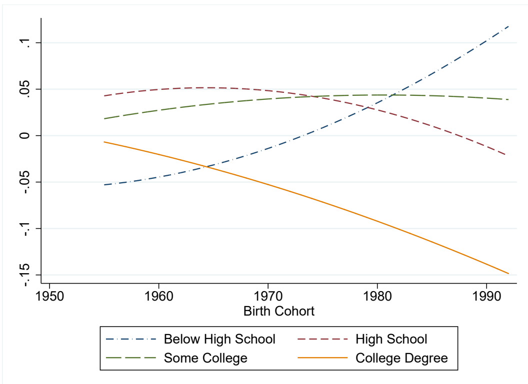
Figure 2.5: Family Premia for Education Levels



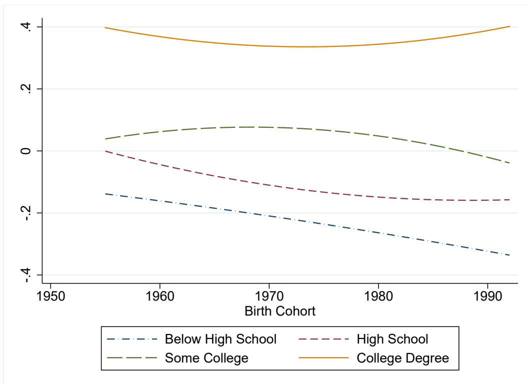
(a) Less than High School



(b) High School



(c) Some College



(d) College Degree

Notes: The figure shows family premia dependent on educational background of the head for the PSID sample. The four panels present the family premia for a given level of educational attainment. Calculations of these premia are based on Checchi et al. (2013). Panel (a) depicts the family premia for less high school dropouts, panel (b) for high school graduation, panel (c) for some college, and panel (d) for college graduation.

Finally, panel (d) shows the family premia for a college degree depending on parental education. The first observation is that there is a strong level difference between family premia, in particular between those with parental college background and all other education levels. Further, over time this gap seems to widen. In other words, children in the

1980s experience a stronger family penalty when trying to obtain a college degree if their parents do not have a college degree themselves. Further, the family premium for children with parents holding a college degree is rising slightly over time after taking a dip until the 1970s birth cohorts. The latter is a clear prediction of the model as it indicates stronger "stickiness" for the upper tail of the education distribution. However, the model also predicts higher transition from secondary to tertiary education. This holds true until the 1970s cohorts, but the family premium has been declining since. This lack of increasing chances to obtain a college degree if the parents do not possess one by themselves can have severe consequences in terms of upward mobility as Altonji and Zhong (2020) illustrate how college degrees are crucial in terms of income.

Overall, the findings on educational polarization mirror the predictions from the model laid out in Section 2.2. It becomes increasingly difficult for children from parents without a college degree to obtain one themselves as shown by the family premia, based on Checchi et al. (2013), for this degree, while the chances have improved for children whose parents are college graduates. Investigating educational polarization with the family of indices by Naga and Yalcin (2008) also confirms most predictions from the model. First, polarization is falling for children whose parents are college graduates, indicating that children with this educational background tend to have less degrees outside of college degrees as well. While there is no indication of rising educational polarization for children from less educated parental backgrounds with equal weights across the whole distribution, polarization is rising when either the lower or the upper tail are more weighted. Lastly, the latter is rising stronger, in line with empirical evidence, e.g. Autor and Dorn (2013), that wages for high-skilled workers rose stronger than those wages for low-skilled workers.

2.4.3.3 Regional Educational Polarization

This section presents empirical evidence that the local decrease in routine jobs leads raises the probability of young labor force participants to make more "extreme" educational choices. However, the advantage of adding geographic variation comes at the expense of not being able to retrieve information about the parental background. I compute the five indices of educational polarization from Table 2.6 for all commuting zones for the census years between 1970 and 2018. To determine the effect of labor market polarization, I estimate a similar model as for upward mobility in equation (2.18). The estimation equation takes on the following form:

$$EducPolarization_{jt} = \beta_0 + \beta_1 \Delta Routine_{jt-1} + X_{jt-1}\Theta + \gamma_t + \gamma_s + \varepsilon_{jt}, \tag{2.22}$$

where $EducPolarization_{jt}$ denotes educational polarization indices of labor force participants between 20 and 29 in commuting-zone j in census year t. Educational polarization is explained by the change in local routine employment during the previous decade, i.e. before the individuals whose educational choice I measure actually enters the labor market. I include a vector of controls (also expressed as 10-year changes) based on the control variables by Autor and Dorn (2013).[16]

The estimation accounts for the median-preserving property of the polarization indices in two ways. First, I limit the sample to commuting-zones where median education is equal to the national mode of median educational across commuting-zones in a given year. I choose the national mode over the national median because it maximizes the number of commuting-zones in the sample. Second, I include time-fixed effects (γ_t), meaning that I only exploit within-period variation when determining the impact of the decline in routine employment on educational polarization. Further, state-fixed effects (γ_s) capture differences in the institutional framework, e.g. the age of compulsory schooling, ranging from 16 to 18. This can have implications on high-school dropout rates, which would imply stronger educational polarization.

The parameter of interest in this regression is β_1, which, according to the model, should be *negative* as a weaker decline in routine occupations implies less extreme education decisions. For comparability across indices and better interpretation of the coefficients, I normalize both the polarization indices and the change in routine employment.

Table 2.7 shows the results based on estimation equation (2.22) with the five different measures of educational polarization in columns (1) to (5). The panels differ in their estimation strategy, the upper one shows the OLS results, and the lower shows the results for the IV estimation strategy.

Both panels show that there is a negative impact of the 10-year change in routine employment on educational polarization of young labor force participants in the OLS estimation. In other words, the weaker labor market polarization in a commuting zone, the less polarized are education outcomes of young labor force entrants. In magnitudes, the point estimate in the first column in panel B a one-standard deviation decrease in routine employment raises the polarization index by 1.09 standard deviations. The coefficients are negative for all indices. Surprisingly, they are smaller for both ANY indices stressing the upper part of the distribution, i.e. ANY(2,1) and ANY(4,1) in columns (2) and (4), respectively. The difference in the point estimates indicates that young labor force participants are more likely to choose lower education levels in response to stronger labor market polarization. They also choose higher levels of educational attainment, albeit a lower rate.

Panel B shows the OLS estimates, where I use the covariates are expressed as lagged levels. Compared to Panel A, the point estimates are smaller in size, around the factor of 3.5. A one percentage point decrease in routine employment over 10 years increases

[16] I exclude the ratio of college to non-college population as this educational polarization is a similar measure to this ratio, but focuses on the young labor force participants.

Table 2.7: Education Polarization and Changes in Routine Employment

	(1) AF	(2) ANY(2,1)	(3) ANY(1,2)	(4) ANY(4,1)	(5) ANY(1,4)
	Panel A - OLS - Covariates as Differences				
Δ Routine	-0.28***	-0.44***	-0.40***	-0.48***	-0.42***
	(-7.70)	(-10.41)	(-10.01)	(-10.16)	(-10.50)
R^2	0.65	0.50	0.58	0.45	0.54
	Panel B - OLS - Covariates as Lagged Levels				
Δ Routine	-0.08***	-0.13***	-0.12***	-0.13***	-0.12***
	(-3.29)	(-4.95)	(-4.64)	(-4.85)	(-4.89)
Obs.	3543	3543	3543	3543	3543
F-Statistic					

Notes: This table estimates the impact of changes in routine employment per working-age population on various indices of educational polarization on the commuting-zone level for the workforce between 20 and 29. Commuting zones are chosen such that their median is equal to the national median in order to maximize the number of observations. Panel A shows the OLS results measuring the covariates as changes, and Panel B shows the OLS results measuring the covariates in (lagged) levels. Year- and state-fixed effects are not shown. Observations are weighted by population share in 1970. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

educational polarization at least 10 percent of a standard deviation for all polarization indices.

2.4.3.4 Individual Education Choices

In the final part of my analysis of educational decisions, I consider individual level data on education from the Current Population Survey (CPS) and merge it with state-specific declines in routine employment from the Decennial Censuses. This approach is equivalent to Ferriere et al. (2020), who investigate individual education decisions in the case of detrimental labor market shocks in the form of Chinese import competition. I estimate the linear probability model

$$e_{ist} = \sum_{q=1}^{4} \beta_q \mathbb{1}_{\{Y_{irt} \in q\}} \Delta Routine_{st} + \delta_e \sum_q \bar{e}_{qst-1} + \gamma_s + \gamma_t + \varepsilon_{ist}, \tag{2.23}$$

where e_{ist} denotes the individual education decision of individual i in state s at time t. I focus on four education decisions, namely high-school dropout, high-school graduation, some college and college. College combines both college enrolment and college degree.[17]

[17] The individual graphs are qualitatively unchanged compared to the graph combining both education outcomes.

$\mathbb{1}_{\{Y_{irt} \in q\}}$ denotes an indicator function with value 1 whenever individual i's household income is in quartile q of the overall income distribution. In order to account for peer effects, $\bar{e}_{qst-1}$ measures the fraction of each income quartile with the same educational decision at $t-1$. γ_s and γ_t indicate state- and time-fixed effects.

The parameters of interest are β_1 to β_4. Each β_q provides information how the decline in routine employment in the previous decade affects the educational decision over all individuals conditional on the individual located in income quartile q. I expect the β_q point estimates to indicate that extreme educational choices are less probable if labor market polarization is weak. For example, I expect β_1 to be negative if the dependent variable is high-school drop-out. A negative sign would imply that children from families located in the first quartile of the income distribution are less likely to drop out of high-school if labor market polarization is weak. Analogously, I expect β_4 to be negative if the college is the outcome variable.

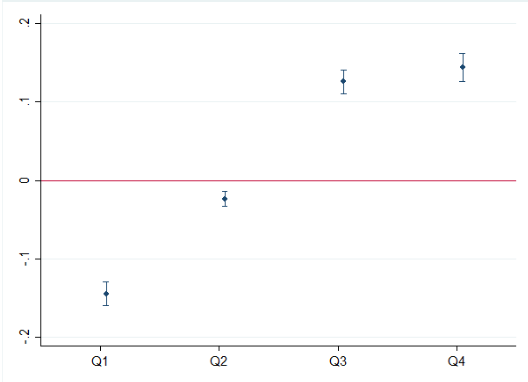
Figure 2.6 shows the coefficient estimates of the linear probability model with four different educational choices. The coefficient plots allow for two comparisons. First, each graph compares how labor market polarization impacts the likelihood across children from all income quartiles ($Q1$ to $Q4$) to choose a given level educational attainment. The second comparison is to compare the point estimates for children from a given quartile and how labor market polarization affects all education choices.

The coefficient plots reveal that the labor market polarization has a similar impact on most education outcomes of the lower two quartiles. The upper two panels provide evidence that children who grow up in families below median income are less likely to choose either dropping out or finishing high-school if labor market polarization is weak. In other words, if the decline in routine-income jobs in the state where children is small before children enter the labor market, the children from parents with below-median income are less likely to choose lower levels of education, specifically to drop out or graduate from high-school. Instead, they are more likely to choose higher education levels, albeit one important difference exists. Children from the lowest quartile are more likely to attain some college education, whereas children from the second quartile are more likely to be enrolled in college or have a college degree.

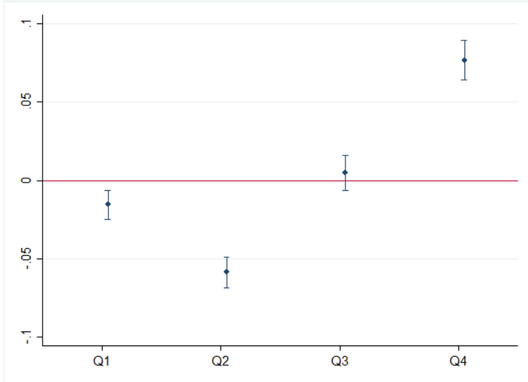
Labor market polarization also impacts the education choices of children from families above median income. Comparing all four panels, children from more affluent parents are less likely to choose the highest level of education if labor market polarization is weak, i.e. if the decline in routine employment is small. Surprisingly, they are more likely to drop out of high-school, and in the case of children from the highest income quartile, also to graduate from high-school or to obtain some college education if labor market polarization is weak. The strength of the decline in routine employment does not have a significant impact on children from the third quartile to obtain high-school education.

Overall, the results of the linear probability model indicate stronger “education sticki-

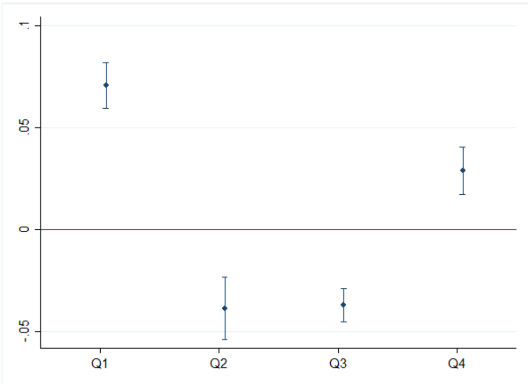
Figure 2.6: Individual Education Choices



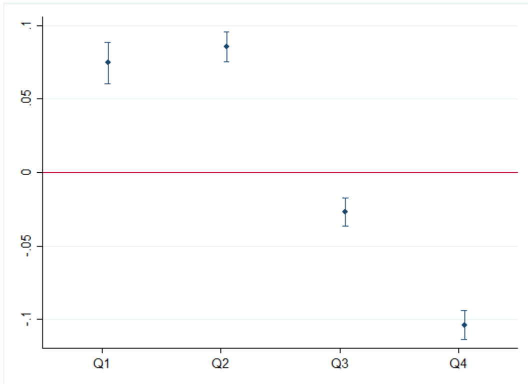
(a) High-School Dropout



(b) High-School Graduation



(c) Some College



(d) College

The coefficient plots show the point estimates of the linear probability model in equation (2.23) for various education choices. In the top left panel the dependent variable is a binary indicator of high-school dropout, and in the top right panel the dependent variable is a binary variable of high-school graduation. The bottom panels focus on college education, with the left one on some college education, and in the right panel the education decision relates to college enrolment and degree.

ness" if labor market polarization is high. With a strong decline in routine employment in the state where children live in before they enter the labor market, the probabilities to choose extreme educational attainment levels more similar to their parental background increases.

2.4.4 Qualifying Predictions

This section confronts the remaining predictions with the data. First, the model also makes predictions how locations differ with respect to housing prices, demand for capital and thick tails. Specifically, the model predicts that high-productivity locations have higher populations and housing prices, demand more capital and exhibit thick tails. With the additional assumption of same area across locations, higher population also translates into higher density. In a second step I confirm that high-income parents provide more support to their children, both in absolute and relative terms. Therefore, the assumption of financial support proportional to parental income is conservative. Relaxing this assumption would reinforce the model predictions obtained in Section 2.2.

2.4.4.1 ICT Investment, Housing Prices and Thick Tails

First, I investigate the spatial pattern of demand for computer capital with respect to log density. One of the key model predictions relates to productivity and density. The more productive location has a higher population size, and with the assumption of the same area, is also more densely population. Therefore, I use log density to represent productive regions.

The model predicts that locations with higher density demand more capital due to larger absolute number of workers in routine occupations. If the relationship between capital demand and historical density is positive, then historical density serves as a good predictor for the rise of ICT capital. Capital also performs routine tasks, and therefore replaces routine workers and makes investment in secondary education less profitable.

I measure ICT investment per worker, which is more forward-looking compared to actual computer adoption or IT budget per worker. Other studies, such as Beaudry et al. (2010) and Autor and Dorn (2013), use computer adoption, though there is likely a strong positive correlation between ICT investment and computer adoption. Eeckhout et al. (2019) use establishment-level data at the MSA ("Metropolitan Statistical Area") in order to measure IT budget per worker. In order to measure ICT investment per worker for each commuting-zone, I apportion ICT investment to the region according to its share of national industry employment, i.e. shift-share measure:

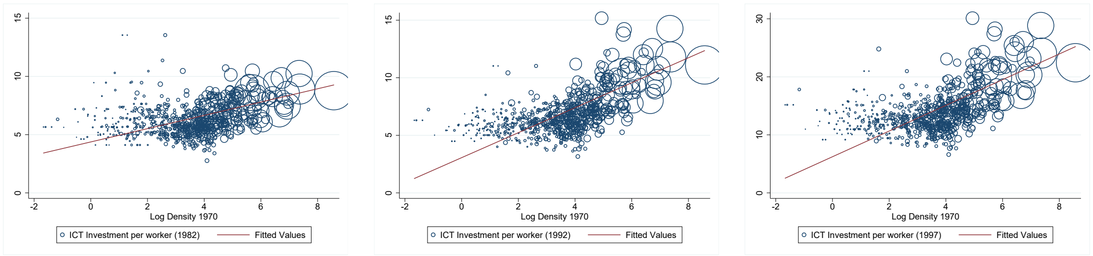
$$ICT_{jt}^{PW} = \sum_k \frac{L_{kjt}}{L_{kt}} \frac{ICT_{kt}}{L_{jt}}. \tag{2.24}$$

In this equation, L_{jt} measures total employment in location j in year t, and ICT_{kt} denotes total ICT investment in industry k in year t. The first fraction is a weighting factor, which exploits variation in the local employment structure. The variation arises mainly from the differences in ICT-using industries across commuting zones.

Figure 2.7 measures plots the relationship between historical log density and ICT investment per worker for three different years, namely in 1982, 1992 and 1997. For comparability across time, I measure ICT investment per worker in 2010 USD. It is visible that ICT investment increases over time, in line with the IT boom in the 1990s. The unit of observation is the commuting zone in the United States. Observations are weighted by the share of population relative to the whole population in the United States in 1970.

All three scatter plots show a positive and economically meaningful relationship between ICT investment and historical density. Over time, i.e. across the three scatter plots, the relationship between historical density and ICT investment per worker increases. In

Figure 2.7: Density and ICT Investment



(a) ICT investment 1982 (b) ICT investment 1992 (c) ICT investment 1997

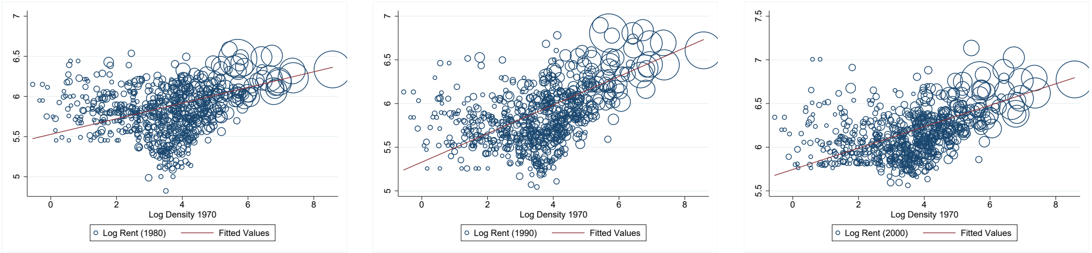
The scatter plots show the correlations between historical levels of density (expressed by its log) and ICT investment per worker in various years on the commuting-zone level. As expected from the model, the slope is positive. Observations are weighted by their 1980 population share.

the left panel, the slope is equal to .57 and statistically significant at all conventional levels. This means that an increase of density by 1% is associated with an increase of 5.70 USD (in 2010 value) of ICT investment per worker. The slope coefficient nearly doubles comparing ICT investment in 1982 and 1992, and more than doubles again between 1992 and 1997. In total, it nearly increases by 4 times in real terms between 1982 and 1997. This is reflective of the strong investment boom in the late 1990s prior to the Dotcom bubble burst in 2001. The graphs show that this investment boom largely concentrates in areas with high density and high human capital. This is true especially given the surprisingly large R^2 of around .5 in five out of the six correlations, with the exception of ICT investment and density in 1982 with a value of .34. The strength of the relationship is based on regressions applying the same weights and are shown in table 2.E1 in Appendix B.

Another model prediction relates to housing prices, specifically the model predicts higher housing prices in the more productive location. This is because individuals are geographically mobile without relocation costs and therefore utility is equal for all individuals with a given educational level. This assumption leads to real wage equalization across locations. As equations (2.5a) to (2.5c) indicate, wages depend on location-specific productivity levels. Therefore, housing prices need to be higher in the more productive, and therefore larger, location.

Figure 2.8 shows the relationship between average commuting-zone rental costs and historical (log) density for three different census years, where information on rents is available. In line with the model prediction, the slopes are positive in all three scatter plots. I show the relationship between rents and historical density because less low-income families own real estate, therefore rental costs are a better approximation for them. However, due to the strong relationship between local rental costs and local housing prices, the correlation between housing values and historical density is also positive. The scatter plots for the same years are shown in Figure 2.E1 in Appendix B.

Figure 2.8: Density and Rents

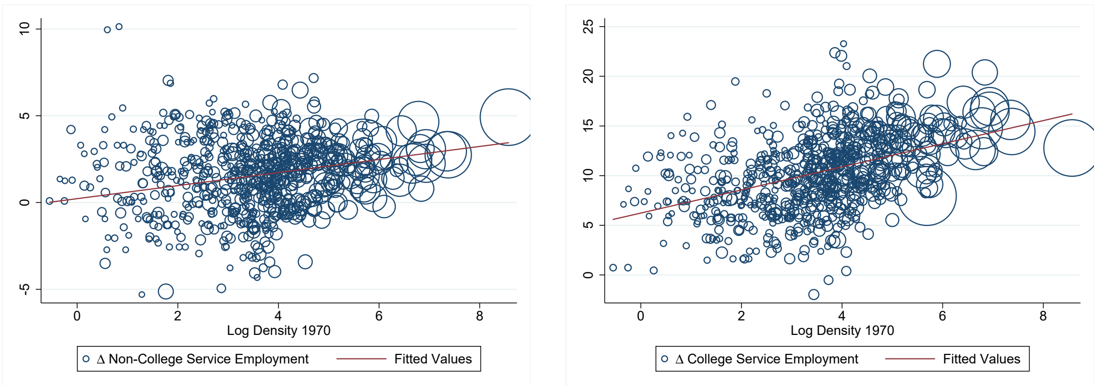


(a) Rents 1980 (b) Rents 1990 (c) Rents 2000

The scatter plots show the correlations between historical levels of density (expressed by its log) and rents in various years. As expected from the model, the slope is positive. Observations are weighted by their 1980 population share.

The last model prediction refers to thick tails. The rising capital stock reduces the returns to routine employment. As individuals decide on their educational attainment based on future wage ratios, they increasingly choose either primary or tertiary education. Subsequently, they work in either manual or abstract occupations, while the number of workers of routine tasks is shrinking. As shown above, high-productivity locations demand more capital, and therefore the share of manual and abstract workers should increase stronger in high-density commuting zones. To test this prediction, I relate the changes in college and non-college service employment to historical density.

Figure 2.9: Density and Thick Tails



(a) Non-College Service Employment (b) College Service Employment

The scatter plots show the correlations between historical levels of density (expressed by its log) and thick tails on the commuting-zone level. The left panel shows the change in non-college service employment between 1970 and 2010 on the vertical axis, while the right panel depicts change in college service employment between 1970 and 2010 on the vertical axis. As expected from the model, the slopes are positive. Observations are weighted by their 1980 population share.

Figure 2.9 shows that the tails of the occupational distribution are increasing stronger in high-density commuting zones. The left panel relates the change in non-college service (manual) employment between 1970 and 2010 with log density in 1970. In line with the model prediction, the slope is positive. The right panel plots the change in college service (abstract) employment against historical density. The slope is also positive, and stronger than for the change in non-college service employment. The model predicts equal changes across locations, but this is the result of the simplifying assumption of symmetry between manual and abstract employment.

2.4.4.2 Intergenerational Transfers

I conjecture that parents bequests the same proportion of their income to their children independent of their occupation, and hence income. Previous work on bequest motives across the income distribution, e.g. Menchik and David (1983) have established that richer parents tend to bequest more to their children. In the model, this assumption leads to more equal chances of children from low- and middle-income parents. In other words, it increases the chances of children whose parents work in manual or routine occupations to attain tertiary education and to experience upward mobility with respect to education, occupation and income.

In order to test the assumption, I make use of two supplemental studies from the PSID, i.e. the "Transfers Module" in 1988 and the "Rosters and Transfer Module" in 2013. They contain information on money given to children (in USD) and on how many hours parents help their children. I can link both supplemental studies to other information in the PSID and determine exact intergenerational transfers and how they differ by parental occupational group. Importantly, I investigate both absolute and proportional pecuniary support from parents to their children. I compute the proportional share of money support to their children relative to the definition of permanent income, i.e. I use parental income when children were between 13 and 19.

Tables 2.8 and 2.9 depict parental income, money support from parents in dollars and in percent, and time help. The latter also includes information on the share of parents provide pecuniary support to their children in school. Consistent with the ranking of wages in the model, average parental income is highest for abstract occupations, and followed by routine and manual occupations. Similarly, children get more money in absolute terms in this ranking in 1988, whereas there is a small difference in 2013 where children from parents working in manual occupations receive more absolute money on average. Money support relative to permanent income during teenagehood does not indicate that the assumption is strongly violated, i.e. they are mainly in line with the previous literature: richer parents tend to spend more on their children.[18] The percentage in columns (3) is not equal to the proportion of money support in column (2) to parental income in column (1), but instead this reflects the average proportional change of the full sample available in each supplemental study.

[18] There is a small discrepancy from these findings in relative support for children from routine parents relative to abstract parents in 1988, but the difference is not large.

Table 2.8: Parental Transfers to Children (1988)

Occupational Group	(1) Parental Income	(2) Money from Parents (USD)	(3) Money from Parents (%)	(4) Time Help from Parents
Manual	51458.7	249.26	.48	141.08
Routine	57737.93	529.89	.88	104.69
Abstract	80211.02	613.73	.81	72.37

Notes: This table shows parental income and transfers of time and money to their children. It shows that income is rising with occupational group, and so are monetary transfers by parents, both in absolute and percent. Help in terms of hours declines with occupational groups. The data is taken from the in 1988 by the PSID.

Columns (4) and (5) in Tables 2.8 and 2.9, respectively, show the average time support in hours for the full calendar year by parental occupation. Interestingly, this relationship across groups has completely flipped over time. In 1988, the relationship of money support (in USD) and time was inverse, that is the less money parents gave to their children for support, the more hours they helped their children. By 2013, this has changed, i.e. parents providing the most support in terms of money also provide the most support in terms of hours.

Table 2.9: Parental Transfers to Children (2013)

Occupational Group	(1) Parental Income	(2) Money from Parents (USD)	(3) Money from Parents (%)	(4) Support School (%)	(5) Time Help from Parents
Manual	57762.11	498.14	.74	15.54	77.12
Routine	63677.86	493.03	.82	19.74	80.69
Abstract	91012.91	1049.54	1.08	34.87	85.81

Notes: This table shows parental income and transfers of time and money to their children. It shows that income is rising with occupational group, and so are monetary transfers by parents, both in absolute and percent. Help in terms of hours declines with occupational groups. The data is taken from the in 2013 by the PSID.

Finally, Table 2.9 shows the share of parents supporting their children in school. The question in the supplemental PSID study asks *whether* parents support their child in school. A clear ranking in line with the wage ranking in the model and in the table is evident, namely a much larger share of parents with abstract occupations support their children in school compared to parents in manual and routine occupations. This is probably driven by stronger educational attainment for children from high-income parents and stronger financial support, and therefore already indicative of a sticky upper tail. The difference between support for educational attainment between routine and manual parents is not as large, but still sizeable.

2.4.5 Robustness Analysis

Dauth (2014) argues that there is no good measure of labor market polarization. In the baseline estimations, I measure labor market polarization with changes in routine employment because it is the most remarkable consequence of routine-biased technological change. In line with Autor and Dorn (2013), I proxy labor market polarization using the rise in non-college service employment.

Table 2.10: Effect of labor market polarization on upward mobility

I. 2nd Stage	(1)	(2)	(3)
	OLS	OLS	IV
Δ Non-College Svc. Emp.	-0.92***	-0.26***	-2.17***
	(-5.05)	(-3.02)	(-4.01)
State FE	No	Yes	Yes
Controls	No	Yes	Yes
Obs.	693	693	693
R^2			
F-Statistic			20.73
II. 1st Stage			
Log Density (1970)			0.24***
			(4.07)
Routine Emp. (1970)			0.04***
			(3.38)
Partial R^2			

Notes: The dependent variable of the second stage of the IV approach is absolute upward mobility regressed on labor market polarization measured as the change in non-college service employment between 1990 and 2010. The lower panel shows the first-stage results. Control variables and state fixed effects are not shown. Observations are weighted by population share in 1980. t-statistics are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table 2.10 shows the results for equations (2.18) and (2.19) using an alternative proxy for labor market polarization. As this proxy is rising with labor market polarization (opposite to changes in routine employment), I expect the opposite sign of the estimated coefficient β_1 compared to the benchmark results, i.e. the sign of the coefficient should be negative if labor market polarization has an adverse impact on intergenerational mobility. Comparing the OLS results in Table 2.10 with those in Table 2.3, the magnitudes are very similar, albeit the point estimates with changes in non-college service employment are slightly larger. Comparing columns (1) and (2) of Tables 2.3 and 2.10, the magnitude of the point estimates in the latter are 19% and 13% higher than in the former.

The crucial difference between Tables 2.3 and 2.10 is visible in the instrumental variable estimation in column (3) of each table. The point estimate of the IV identification strategy is increasing (in magnitude) by much more in the robustness analysis compared to the benchmark estimation. While the OLS results are biased towards zero, the increase in the point estimates from column (2) to column (3) is unusual. The first-stage results do not indicate any weakness in terms the F-statistics or either the signs or statistical significance. The F-statistic is well above 10, and the point estimates of the first-stage in the lower panel indicate that the instruments, in line with expectations, raise the share of non-college service employment.

In order to confirm the results obtained above, I use two further measurements of intergenerational mobility taken from Chetty et al. (2014). The first is relative upward mobility, which measures the expected rank of children from the richest versus the poorest families. This means that it behaves opposite to absolute upward mobility, i.e. a higher value implies a lower degree of intergenerational mobility. Consequently, the expected sign for the estimated coefficient of β_1 in equation (2.18) turns negative, i.e. the less strong labor market polarization, the smaller the distance between the expected ranks from families at the top and bottom of the income distribution. The second measure is the probability of an intergenerational transition between the lowest income quintile and the highest income quintile. This measure is, just like the benchmark results, from the perspective of children from low-income families, hence the parameter β_1 should be positive (again).

Because the first-stage results the same as in Tables 2.3 and 2.4, Table 2.11 only presents the results of the OLS regression and for the second stage of the IV estimation strategy. For most specifications, the point estimate is - as expected - positive, indicating that in commuting zones with stronger labor market polarization kids from top-income parents experience higher expected ranks relative to children from low-income parents. As argued above for absolute mobility, endogeneity is also a concern in these estimation, leading to a downward bias for relative mobility (due to its inverse behavior) and an upward bias for the quintile transition probability. Using the point estimate in column (2) of panel A, a one percentage point increase in polarization (measured by a decline in routine employment) leads to an improvement of .53 ranks of children of the richest parents compared to children from the poorest. The point estimates in panel A indicate that children from the highest-ranked families profit more from labor market polarization than children from the lowest-ranked families. Precisely, the difference in percentiles of children from the lowest-ranked families and from the highest-ranked is equal to 4.09 percentiles comparing commuting zones without labor market polarization to the median-hit commuting zone. One reason why this is smaller than for the baseline results for children at the 25^{th} percentile is that wages also changed non-monotonically. Autor and Dorn (2013) actually show that wage losses were the highest for parents at the 25^{th} skill percentile, whereas workers below this skill percentile sometimes even experienced wage increases.

Panel B in Table 2.11 use the probability for a child reaching the highest quintile in the income distribution conditional on his parents being located in the lowest quintile show that labor market polarization also has a detrimental impact. Excluding the specification with the first principal component of segregation, the sign is negative in all specifications and statistically significant. Considering the point estimate of column (2), it shows that a

Table 2.11: Robustness analysis: Effect of labor market polarization on upward mobility

I. 2nd Stage	(1) OLS	(2) IV	(3) MIG	(4) LAB	(5) COL	(6) TAX	(7) FAM	(8) SOC	(9) K12	(10) INC	(11) SEG	(12) BLA
Panel A - Relative Mobility												
Δ Routine Emp.	-0.15***	-0.53***	-0.42***	-0.50***	-0.48***	-0.57***	-0.07	-0.61***	-0.44**	-0.61***	0.10	-0.24
	(-2.59)	(-3.30)	(-2.65)	(-3.05)	(-2.85)	(-3.68)	(-0.51)	(-3.71)	(-2.09)	(-2.73)	(0.55)	(-1.61)
Obs.	693	693	691	693	563	693	693	666	663	693	693	693
F-Statistic		122.32	113.67	125.91	110.47	114.48	104.76	100.44	78.24	61.21	46.59	105.68
Panel B - Transition Probability (P1, K5)												
Δ Routine Emp.	0.16***	0.44***	0.43***	0.44***	0.40***	0.18**	0.48***	0.43***	0.37***	0.63***	-0.04	0.36***
	(4.52)	(4.44)	(4.18)	(4.37)	(3.99)	(2.16)	(4.48)	(4.09)	(2.60)	(4.70)	(-0.33)	(3.78)
Obs.	693	693	691	693	563	693	693	666	663	693	693	693
F-Statistic		122.32	113.67	125.91	110.47	104.76	114.48	100.44	78.24	61.21	46.59	105.68

Notes: This table replicates the regression results from Tables 2.3 and 2.4, but exploits alternative measures of intergenerational mobility. Panel A uses relative mobility, while Panel B uses the probability of a child to be in the top quintile (K5), while parents were located in the lowest quintile (P1). Both measures are taken from Chetty et al. (2014). As before, MIG stands for migration, LAB for labor markets, COL for college, TAX for the tax system, FAM for family, SOC for social capital K12 for high-school, INC for properties of the income distribution, SEG for segregation, and BLA for fraction of black population. Control variables and state fixed effects are not shown. Observations are weighted by population share in 1980. t-statistics are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

one percentage point increase in routine employment reduces the transition probability by 0.44 percentage points. 3.42% more of the children from families in the lowest quintile of the income distribution in commuting zones without labor market polarization would reach the highest income quintile compared to children from the median-hit commuting zone. This difference is nearly equal to the difference between the 25th and the 75th of this mobility measure (3.85%).

2.5 Conclusion

Does labor market polarization limit the equality of opportunity for children from low-income parents? To understand the relationship between both phenomena, I set up a simple theoretical framework drawing on existing models on educational choice and labor market polarization. The model features substitutability between routine employment and capital and exogenous location-specific productivity differences. The education decision of the young generation depend on future wage ratios and parental bequests. Due to the substitutability between routine labor and capital, a rising capital stock reduces the returns to routine employment. Location-specific productivity differences impact local demand for capital, hence the decline in routine employment is stronger in high-productivity regions. The model also predicts that more productive regions are larger and more dense.
Subsequently, I take the model predictions to the data. The key model prediction relates to upward mobility of children from low-income parents. The decline of both routine wages and jobs reduces the chances of children to climb the economic ladder. I estimate the impact of labor market polarization on absolute upward mobility from Chetty et al. (2014) exploiting commuting-zone variation in the United States. To tackle various endogeneity issues I estimate the causal impact with an instrumental variable estimation strategy. Based on the model and the previous literature, I use (log) density and the historical share of routine employment before the arrival of the first commercially successful personal computers as an instrumental variable. The results provide evidence that labor market polarization substantially reduces the expected rank for children whose parents are located at lower parts of the income distribution.
Using intergenerational elasticity as another measure of intergenerational mobility, I show that the model prediction over time also holds in the data. With less intergenerational transitions out of manual and abstract occupations, the model predicts a rising IGE for these two groups. On the other hand, for children whose parents work in routine-intensive occupations, parental income the model predicts a lower importance of parental income as they transition into both manual and abstract occupations. I exploit information on children and their parents from the PSID and test these model predictions. This pattern holds overall in the data, and the pattern evolves over time as labor market polarization progresses. However, the main changes in intergenerational elasticity take place for children

from both routine and abstract occupations, whereas IGE stays at a similar level for children with parents in manual occupations.

The empirical evidence supports that the importance of the education channel via which labor market polarization reduces intergenerational mobility. First, I provide evidence that education of young labor market entrants has become more polarized over time in the United States. Second, I compute family premia for different levels of educational attainment, which suggest rising stickiness with respect to education. Third, I show that a decline in routine jobs raises local educational polarization for panel of commuting zones. The results suggest that labor market polarization drives extreme educational choices at both tails of the distribution. In the fourth and final step I estimate how labor market polarization affects individual educational choice depending on parental income. The findings support the notion of educational stickiness if labor market polarization is strong.

One concern with this paper is to ask whether the results also hold in countries where tuition fees are low or equal to zero. While the model assumes pecuniary bequests, Mayer et al. (2019) underline that other factors such as parental support and encouragement also matter for the decision on educational attainment. If non-pecuniary elements also matter for educational attainment, then the results of this study are likely to hold in other countries as well. For example, Landersø and Heckman (2017) argue that the mobility pattern between Denmark and the United States is "remarkably similar", whereas Andrade and Thomsen (2018), using the same data, conclude that mobility is substantially higher in Denmark. The data on regional upward mobility for Italy by Güell et al. (2018) combined with data on regional labor market polarization can provide insights into whether the results change substantially as tuition fees in Italy are much lower than in the United States.

Overall, these findings are important for a variety of reasons. First, the findings in this paper contend with the notion that neighborhood is the main explanatory factor of intergenerational mobility as argued in Chetty and Hendren (2018a) and Chetty and Hendren (2018b). Instead, it highlights the role of labor markets as suggested by Rothstein (2019). Secondly, the paper highlights the role of structural transformations, subsequent wage declines for certain occupations, and how the next generation with parents who work in these vulnerable occupations is affected. Therefore, in order to allow children from all background to achieve their potential, it is crucial to identify vulnerable occupations during structural transformations, e.g. for the future the rise of robots as documented by Graetz and Michaels (2018) and Acemoglu and Restrepo (2020). Third, the findings indicate that segregation by race and/or income can also play a role, in line with findings by Fogli and Guerrieri (2019) and Chetty et al. (2020).

Appendix A

2.A Polarization over time

As this appendix concentrates on how rising capital stock in the economy affects educational choices over time, I drop the subscript j from the notation here. All derivations hold for all locations, independent of their difference in exogenous productivity A_j.
The exogenous driving force in the model is the technology parameter of capital ζ_t. Given the assumed production cost of this intermediate good, it is equal to price of capital (p_{kt}). The capital stock rises with falling technology parameter $zeta_t$. Importantly, if the technology parameter is sufficiently large, there won't be any capital produced, and the economy produces the final good with three factors of production, i.e. manual, routine and abstract labor.
A rising capital stock in the economy detrimentally impact routine wages, but affect neither manual or abstract wages:

$$\partial w_{mjt} = 0 \tag{2.25a}$$

$$\partial w_{rjt} < 0 \tag{2.25b}$$

$$\partial w_{ajt} = 0 \tag{2.25c}$$

Individuals take into account wage ratios when making their choice on education as seen in equations (2.11) to (2.16). The three wage ratios of importance react distinctly on a rise of capital (induced by falling price of capital):

$$\frac{\partial(w_{mjt}/w_{ajt})}{\partial K} = 0 \tag{2.26a}$$

$$\frac{\partial(w_{mjt}/w_{rjt})}{\partial K} > 0 \tag{2.26b}$$

$$\frac{\partial(w_{rjt}/w_{ajt})}{\partial K} < 0 \tag{2.26c}$$

Based on the assumption of substitutability between routine labor and capital, i.e. ($\gamma_r < \theta$), these comparative statics show that how the rise of the capital stock changes wage ratios and therefore the thresholds of educational frictions.
For example, the threshold of educational frictions with respect to the choice between routine and manual employment, i.e. secondary or primary education, is defined in equation (2.11) as:

$$\hat{\tau}_{ijt}^{mr} = x_{mjt}\left[1 - \frac{w_{mjt+1}}{w_{rjt+1}}\right],$$

where an increase in the wage ratio between manual and routine occupations (induced by falling capital prices) raises the threshold level of educational frictions for which an individual chooses secondary over primary education. Hence, less cross-generational transfers out of manual into routine occupation occur. While transitions from manual into routine occur at a lower rate, this wage ratio also impacts children whose parents work in routine occupations, where an increase in the wage ratio between manual and routine occupations leads to more transitions out of routine into manual employment.
Just the same pattern emerges when considering individuals choosing between secondary and tertiary education, i.e. routine and abstract employment.

$$\hat{\tau}_{ijt}^{ra} = \frac{x_{rjt}\left[1 - \frac{w_{rjt+1}}{w_{ajt+1}}\right]}{z - \frac{w_{rjt+1}}{w_{ajt+1}}},$$

$$\hat{\tau}_{ijt}^{ar} = \frac{x_{ajt}\left[1 - \frac{w_{rjt+1}}{w_{ajt+1}}\right]}{z - \frac{w_{rjt+1}}{w_{ajt+1}}}.$$

2.B Labor Demand

Labor demand for manual and abstract tasks is derived from equation (2.10 and plugging in wages based on the firm maximization problem, i.e. equations (2.5a) and (2.5c). As the argumentation is analogous, I will only derive labor demand for manual tasks in detail. It holds that:

$$L_{m1t} = \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m - 1}} L_{m2t}. \tag{2.27}$$

Further, I use the labor market clearing condition ($L_{it} = L_{i1t} + L_{i2t}\ \forall\ i$), where $i \in (m, r, a)$. Substituting the labor market clearing condition in for L_{m1t} and L_{m2t} separately, yields the following labor demands:

$$L_{m1t} = \frac{\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}} L_{mt}}{1+\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}}} \quad \text{and} \quad L_{m2t} = \frac{L_{mt}}{1+\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}}} \tag{2.28}$$

Analogously, for abstract labor demand:

$$L_{a1t} = \frac{\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}} L_{at}}{1+\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}}} \quad \text{and} \quad L_{a2t} = \frac{L_{at}}{1+\left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}}} \tag{2.29}$$

Labor demand for routine labor in both cities is based on equation (2.5d). Manipulating for each city yields:

$$L_{r1t} = \left\{\frac{1}{A_r}\left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]\right\}^{\frac{1}{\theta}} K_{1t} \tag{2.30}$$

$$L_{r2t} = \left\{\frac{1}{A_r}\left[\left(\frac{p_{kt}}{A_2\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]\right\}^{\frac{1}{\theta}} K_{2t} \tag{2.31}$$

It is important to note that labor demand for manual and abstract depends on the ratios of exogenous productivity levels and the price of housing, whereas demand for routine tasks depends on local exogenous productivity and local capital demand.

2.C Productivity and Housing Prices

This sections proves that housing prices are higher in the more productive region. Starting from the housing equilibrium, where total housing supply H is constant for all locations j:

$$\sum_i h_{ijt} L_{ijt} = H \quad \forall j. \tag{2.32}$$

Substituting the equilibrium allocation for housing ($h^*_{ijt+1} = \frac{\beta w_{ijt+1}}{p_{jt+1}}$) yields:

$$\sum_i w_{ijt} L_{ijt} = H \frac{p_{jt}}{\beta} \quad \forall j. \tag{2.33}$$

Combining this result for both regions, I obtain:

$$\frac{p_{1t}}{p_{2t}} = \frac{w_{m1t}L_{m1t} + w_{r1t}L_{r1t} + w_{a1t}L_{a1t}}{w_{m2t}L_{m2t} + w_{r2t}L_{r2t} + w_{a2t}L_{a2t}}. \tag{2.34}$$

Plugging in wages from equations (2.5a) to (2.5c) and rearranging gives:

$$(A_r L^\theta_{r1t} + A_k K^\theta_{1t})^{\frac{\gamma_r - \theta}{\theta}} A_r L^\theta_{r1t} - \frac{p_{1t}}{p_{2t}} \frac{A_2}{A_1} (A_r L^\theta_{r1t} + A_k K^\theta_{2t})^{\frac{\gamma_r - \theta}{\theta}} A_r L^\theta_{r2t} =$$

$$= \left[\frac{p_{1t}}{p_{2t}} \frac{A_2}{A_1}\right] \left[A_m L^{\gamma_m}_{m2t} + A_a L^{\gamma_a}_{a2t}\right] - A_m L^{\gamma_m}_{m1t} - A_a L^{\gamma_a}_{a1t} \tag{2.35}$$

Plugging in the labor demands for manual and abstract in both regions from Appendix 2.B, and manipulating yields:

$$(A_r L^\theta_{r1t} + A_k K^\theta_{1t})^{\frac{\gamma_r - \theta}{\theta}} A_r L^\theta_{r1t} - \frac{p_{1t}}{p_{2t}} \frac{A_2}{A_1} (A_r L^\theta_{r1t} + A_k K^\theta_{2t})^{\frac{\gamma_r - \theta}{\theta}} A_r L^\theta_{r2t} =$$

$$= A_m \left(\frac{L_{mt}}{1 + \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^\beta\right]^{\frac{1}{\gamma_m - 1}}} \right)^{\gamma_m} \left[\frac{A_2}{A_1}\frac{p_{1t}}{p_{2t}} - \frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^\beta \right]^{\frac{\gamma_m}{\gamma_m - 1}} \Bigg] +$$

$$+ A_a \left(\frac{L_{at}}{1 + \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^\beta\right]^{\frac{1}{\gamma_a - 1}}} \right)^{\gamma_a} \left[\frac{A_2}{A_1}\frac{p_{1t}}{p_{2t}} - \frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^\beta \right]^{\frac{\gamma_a}{\gamma_a - 1}} \Bigg] \tag{2.36}$$

Now I focus on the LHS of equation (2.36) by starting to reconsider the wages for routine in both regions. Combining equation (2.5b) for both regions and the real wage equalization equation (2.10), I can show that:

$$(A_r L_{r2t}^{\theta} + A_k K_{2t}^{\theta})^{\frac{\gamma_r-\theta}{\theta}} = \left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} \frac{A_1}{A_2} (A_r L_{r1t}^{\theta} + A_k K_{1t}^{\theta})^{\frac{\gamma_r-\theta}{\theta}} \left(\frac{L_{r1t}}{L_{r2t}}\right)^{\theta-1} \tag{2.37}$$

Plugging this result into the LHS of equation (2.36) and some rearranging yields:

$$\underbrace{(A_r L_{r1t}^{\theta} + A_k K_{1t}^{\theta})^{\frac{\gamma_r-\theta}{\theta}}}_{\text{A}} \underbrace{A_r L_{r1t}^{\theta}}_{\text{B}} \left[1 - \left(\frac{p_{1t}}{p_{2t}}\right)^{1-\beta} \underbrace{\frac{L_{r2t}}{L_{r1t}}}_{\text{C}}\right] \tag{2.38}$$

Now we can substitute multiple terms from equation (2.38), which is equal to the LHS of equation (2.36) from other parts. Specifically, I concentrate on the first term (A), the second term (B) and the last term in the squared bracket (C). For A, I can use (2.5d):

$$(A_r L_{r1t}^{\theta} + A_k K_{1t}^{\theta})^{\frac{\gamma_r-\theta}{\theta}} = \frac{p_{kt}}{A_1 \gamma_r A_k} K_{1t}^{1-\theta} \tag{2.39}$$

Second, for B, from the labor demand for routine labor in region 1, I get:

$$A_r L_{r1t}^{\theta} = \left(\frac{p_{kt}}{A_1 \gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k K_{1t}^{\theta} \tag{2.40}$$

Third, for C, the derivation is somewhat longer. Starting with the acknowledging that the price for capital is the same for all regions, and therefore using equation (2.10), it holds that:

$$\frac{\frac{w_{r1t}}{p_{kt}}}{\frac{w_{r2t}}{p_{kt}}} = \left(\frac{p_{1t}}{p_{2t}}\right)^{\beta} \tag{2.41}$$

Plugging in the equations (2.5b) and (2.5d) for both regions and rearranging yields:

$$\frac{L_{r1t}}{L_{r2t}} = \left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{\theta-1}} \frac{K_{1t}}{K_{2t}} \tag{2.42}$$

Plugging in labor demands for routine tasks for both locations, i.e. equations (2.30) and (2.31), and rearranging

$$\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{\theta-1}} = \frac{\frac{p_{kt}}{A_1 \gamma_r A_k}^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k}{\frac{p_{kt}}{A_2 \gamma_r A_k}^{\frac{\theta}{\gamma_r-\theta}} K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k} \tag{2.43}$$

Solving for $K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}$ yields:

$$K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} = \left(\frac{A_2}{A_1}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta\theta}{1-\theta}} + \left[1 - \left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta\theta}{1-\theta}}\right] A_k \left(\frac{p_{kt}}{A_2 \gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} \tag{2.44}$$

I am also exploiting the labor market clearing condition for routine labor ($L_{rt} = L_{r1t} + L_{r2t}$), where I also plug in the respective labor demands given in equations. Solving this for K_{2t}, yields:

$$K_{2t} = \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[\left(\frac{p_{kt}}{A_2\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.45}$$

Plugging equation (2.44) into the denominator of equation (2.45) and manipulation gives:

$$K_{2t} = \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{1-\theta}} \left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\theta-\gamma_r}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.46}$$

Plugging equation (2.46) into equation (2.42) and replacing $L_{r2t} = L_{rt} - L_{r1t}$ gives:

$$\frac{L_{rt} - L_{r1t}}{L_{r1t}} = \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}. \tag{2.47}$$

Now that I have found expressions for the terms A, B and C in equation (2.38) shown in equations (2.39), (2.40) and (2.47), respectively, I can plug them into equation (2.36):

$$\begin{aligned}
&\left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\gamma_r}{\gamma_r-\theta}} K_{1t}^{\frac{\gamma_r(1-\theta)}{\gamma_r-\theta}} - \frac{p_{kt}}{A_1\gamma_r} K_{1t}\right] \times \\
&\times \left\{ \frac{\left(1 + \left(\frac{p_{1t}}{p_{2t}}\right)^{1-\beta}\right)\left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t} - \left(\frac{p_{1t}}{p_{2t}}\right)^{1-\beta} L_{rt}A_r^{\frac{1}{\theta}}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\theta-\gamma_r}} - A_k\right]^{\frac{1}{\theta}} K_{1t}} \right\} = \\
&= A_m \left(\frac{L_{mt}}{1 + \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_m-1}}}\right)^{\gamma_m} \left[\frac{A_2}{A_1}\frac{p_{1t}}{p_{2t}} - \frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{\gamma_m}{\gamma_m-1}} + \\
&+ A_a \left(\frac{L_{at}}{1 + \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{1}{\gamma_a-1}}}\right)^{\gamma_a} \left[\frac{A_2}{A_1}\frac{p_{1t}}{p_{2t}} - \frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{\gamma_a}{\gamma_a-1}}
\end{aligned} \tag{2.48}$$

Equation (2.43) is essentially equivalent to Eeckhout et al. (2019, Eq. F.1).
I can now commence the proof for housing prices dependent on productivity advantages in location 1. I am working with contradictions. Assume $A_2 > A_1$ and $p_{1t} > p_{2t}$. This implies that the RHS of equation (2.48) is greater than zero as $\beta \in (0,1)$, so the LHS also has to be greater than zero. The first term in squared brackets is also greater than zero - see equations (2.39) and (2.40) - , so I have to investigate the term in curly brackets in

equation (2.48): For the inequality to hold, it has to be greater than zero, so after some rearrangement, I obtain:

$$K_{1t}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta-1} > \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[\left(\frac{p_{kt}}{A_2\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.49}$$

Dividing the last equation by $\frac{p_{1t}}{p_{2t}}^{\frac{\beta}{1-\theta}}$, this yields:

$$K_{1t}\left(\frac{p_{2t}}{p_{1t}}\right)^{1+\frac{\beta\theta}{1-\theta}} > \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\frac{p_{1t}}{p_{2t}}^{\frac{\beta}{1-\theta}}\left[\left(\frac{p_{kt}}{A_2\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.50}$$

When combining equations (2.44) and (2.46), I obtain:

$$\left\{\frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{1-\theta}}\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}}\right\}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} =$$

$$= \left(\frac{A_2}{A_1}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta\theta}{1-\theta}} + \left[1-\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta\theta}{1-\theta}}\right]A_k\left(\frac{p_{kt}}{A_2\gamma_r A_k}\right)^{\frac{\theta}{\theta-\gamma_r}}. \tag{2.51}$$

This equation is essentially equivalent to Eeckhout et al. (2019, Eq. F.2). I can infer from equation (2.51) that, given the assumptions about exogenous productivity differences and prices, i.e. $A_2 > A1$ and $p_{1t} > p_{2t}$, that the last term is smaller than zero. Consequently it has to hold:

$$K_{1t}\left(\frac{p_{2t}}{p_{1t}}\right)^{\frac{\beta\theta}{1-\theta}\frac{\theta-\gamma_r}{(1-\gamma_r)\theta}} < \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{1-\theta}}\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\theta-\gamma_r}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.52}$$

Equations (2.50) and (2.52) allow me to focus on the exponents of the LHS, respectively. For the assumptions set out at the beginning of the proof (i.e. $A_2 > A_1$ and $p_{1t} > p_{2t}$) to hold, I need that both inequalities hold, indicating that the exponent of equation (2.52) is smaller than that of equation (2.50) given that $\frac{p_{2t}}{p_{1t}} < 1$. Thus, by subtracting the latter from the former, it should give a negative value:

$$1+\frac{\beta\theta}{1-\theta} - \frac{\beta\theta}{1-\theta}\frac{\theta-\gamma_r}{(1-\gamma_r)\theta} = 1+\frac{\beta\theta}{1-\theta}\left(1-\frac{\theta-\gamma_r}{(1-\gamma_r)\theta}\right) = 1+\frac{\beta\gamma_r}{1-\gamma_r} > 0 \tag{2.53}$$

Hence, I get a contradiction from equations 2.50 and 2.52, and it holds that the more productive region has higher housing prices. In formal terms, this proves that $p_{1t} > p_{2t}$ if

$A_1 > A_2$.

I further show that it holds: If $A_1 > A_2$, then $\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} > 1$.
Starting again with equation (2.48) and the squared bracket, and a proof by contradiction, I assume that $A_1 > A_2$ and $\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} < 1$. This assumption implies that the squared bracket is positive, rendering its RHS also greater than 0:

$$\frac{A_2}{A_1}\frac{p_{1t}}{p_{2t}} - \left[\frac{A_2}{A_1}\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\right]^{\frac{\gamma_i}{\gamma_i-1}} > 0, \quad \text{with } i \in \{m,r\}. \tag{2.54}$$

This implies that the LHS of equation (2.48) must also be positive. Following the previous argumentation, the inequality of equation (2.50) also has to hold. Also, in equation (2.51), we know that the last term is negative as $p_{1t} > p_{2t}$. Therefore: Using the RHS of both these equations, and dividing yields:

$$\frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{1-\theta}}\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} > \left(\frac{A_2}{A_1}\right)^{\frac{1}{1-\gamma_r}} K_{1t}\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{1-\theta}\frac{\gamma_r-\theta}{1-\gamma_r}} \tag{2.55}$$

Using the last inequality and dividing it by the last inequality gives:

$$\frac{\text{RHS(2.50)}}{\text{RHS(2.55)}} = \left(\frac{A_1}{A_2}\right)^{\frac{1}{1-\gamma_r}}\left(\frac{p_{2t}}{p_{1t}}\right)^{1+\frac{\beta\theta}{(1-\theta)}\left[1-\frac{\gamma_r-\theta}{\theta(1-\gamma_r)}\right]} \tag{2.56}$$

After some rearranging, I can write the previous equation as:

$$\frac{\text{RHS(2.50)}}{\text{RHS(2.55)}} = \left[\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{1-\gamma_r(1-\beta)}\right]^{\frac{1}{1-\gamma_r}}. \tag{2.57}$$

Analogous to the exercise above of comparing exponents, I can show that: $1-\gamma_r(1-\beta) > \beta$. As $p_{1t} > p_{2t}$, then it holds that:

$$\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{1-\gamma_r(1-\beta)} < \frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} < 1, \tag{2.58}$$

where the last inequality comes from the initial assumption to work towards contradiction. As $\gamma_r \in (0,1)$, then $\frac{1}{1-\gamma_r} > 0$. As a consequence, $\frac{\text{RHS(2.50)}}{\text{RHS(2.55)}} < 0$. This means that both inequalities cannot be satisfied and therefore I have a contradiction.
Formally, this means:

$$\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} > 1. \tag{2.59}$$

2.D Productivity and Population Size

The calculation is the same for both manual and abstract labor, I will show this with the example of manual labor. Labor demand for manual tasks in location 1 is given by equation (2.28):

$$L_{m1t} = \frac{\left[\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta}\right]^{\frac{1}{1-\gamma_m}} L_{mt}}{1+\left[\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta}\right]^{\frac{1}{1-\gamma_m}}} \tag{2.60}$$

As shown in Appendix 2.C, it holds that $\frac{A_1}{A_2} > \left(\frac{p_{2t}}{p_{1t}}\right)^{\beta}$. Using these results for manual labor demand in location 1 yields:

$$L_{m1t} > \frac{L_{mt}}{2}, \tag{2.61}$$

as, by assumption, $\frac{1}{1-\gamma_m} > 1$. This implies that $L_{m1t} > L_{m2t}$ and, as stated above analogously for abstract labor, $L_{a1t} > L_{a2t}$.

Now, location 1 can only be smaller if $L_{r2t} > L_{r1t}$. To show that this is not the case, I will be working with a contradiction.
Re-consider equation (2.51). I have shown that $p_{1t} > p_{2t}$ if $A_1 > A_2$. This means that the second term of this equation is negative, and it holds:

$$\left\{\frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\theta-\gamma_r}} - A_k\right]^{\frac{1}{\theta}}}\right\}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} > \left[\left(\frac{p_{1t}}{p_{2t}}\right)^{\beta}\frac{A_2}{A_1}\right]^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \tag{2.62}$$

Going back to equation (2.47), and using the assumption $L_{r2t} > L_{r1t}$ (implying $\frac{L_{rt}-L_{r1t}}{L_{r1t}} > 1$), it also holds:

$$K_{1t} > \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} \tag{2.63}$$

Manipulation of the previous equation implies:

$$K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} > \left\{\frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}}\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}}\right\}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \tag{2.64}$$

Combining equations (2.62) and (2.64) implies that:

$$K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} > \left\{ \frac{L_{rt}A_r^{\frac{1}{\theta}} - \left[\left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}} K_{1t}}{\left[K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \left(\frac{p_{kt}}{A_1\gamma_r A_k}\right)^{\frac{\theta}{\gamma_r-\theta}} - A_k\right]^{\frac{1}{\theta}}} \right\}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} > \left[\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} \frac{A_1}{A_2}\right]^{\frac{\theta}{\theta-\gamma_r}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \tag{2.65}$$

As shown above, it holds that $\frac{A_1}{A_2}\left(\frac{p_{2t}}{p_{1t}}\right)^{\beta} > 1$. This implies that, as the last term the first term of the third component in equation (2.65) is greater than one as $\gamma_r < \theta$. Hence, I found a contradiction, and it must hold that $L_{r1t} > L_{r2t}$.

Ultimately, it holds that the share of each labor type in location 1 is higher than in location 2, hence it holds that the size of location 1 is greater than that of location 2, i.e. $S_1 > S_2$ as $S_j = \sum_i L_{ijt}\ \forall\ j$.

2.E Productivity and Demand for Capital

Following the proof from Appendix 2.C, i.e. prices are higher in region 1 compared to region 2 ($p_{1t} > p_{2t}$) if $A_1 > A_2$. The price for capital is the same for all regions, therefore, using equation (2.10), it holds: :

$$\frac{\frac{w_{r1t}}{p_{kt}}}{\frac{w_{r2t}}{p_{kt}}} = \left(\frac{p_{1t}}{p_{2t}}\right)^{\beta} \tag{2.66}$$

Plugging in the equations (2.5b) and (2.5d) for both regions and rearranging yields:

$$\frac{L_{r1t}}{L_{r2t}} = \left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{\theta-1}} \frac{K_{1t}}{K_{2t}} \tag{2.67}$$

Plugging in labor demands for routine tasks for both locations, i.e. equations (2.30) and (2.31), and rearranging

$$\left(\frac{p_{1t}}{p_{2t}}\right)^{\frac{\beta}{\theta-1}} = \frac{\frac{p_{kt}}{A_1\gamma_r A_k}^{\frac{\theta}{\gamma_r-\theta}} K_{1t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k}{\frac{kt}{A_2\gamma_r A_k}^{\frac{\theta}{\gamma_r-\theta}} K_{2t}^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} - A_k} \tag{2.68}$$

As shown above, it holds that $p_{1t} > p_{2t}$ if $A_1 > A_2$ and by assumption, $\gamma_r < 1$, then the LHS of equation (2.68) is smaller than 1. Hence, the RHS also has to be smaller than 1. Setting the LHS smaller than zero, and simplifying then yields:

$$\left(\frac{A_1}{A_2}\right)^{\frac{\theta}{\gamma_r-\theta}} > \left(\frac{K_{1t}}{K_{2t}}\right)^{\frac{(1-\gamma_r)\theta}{\gamma_r-\theta}} \tag{2.69}$$

Remember that $\gamma_r < \theta$, hence the inequality sign turns around when cancelling out exponents as far as possible. Then it holds that:

$$\frac{A_1}{A_2} < \left(\frac{K_{1t}}{K_{2t}}\right)^{1-\gamma_r} \tag{2.70}$$

By assumption, if $A_1 > A_2$, the LHS of equation (2.70) is greater than 1. Subsequently, the RHS must also be greater than 1, and as $\gamma_r < 1$, the RHS is only greater than one if $K_{1t} > K_{2t}$.

Consequently, capital demand is higher in the location with higher exogenous productivity.

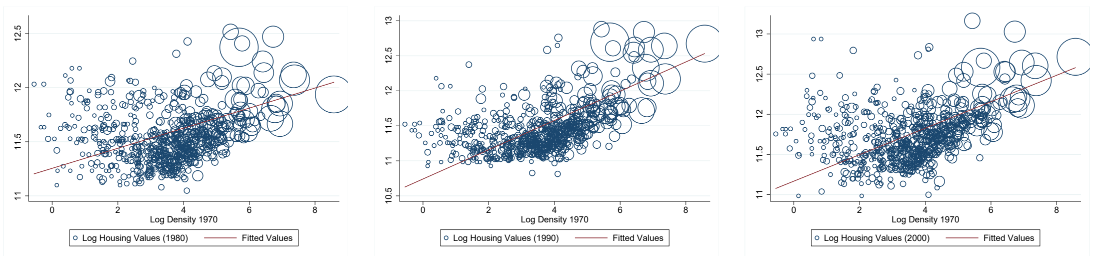
Appendix B - Empirical Evidence I

Table 2.E1: Correlations of Density and Human Capital with ICT Investment per Worker

	(1)	(2)	(3)
Log Population (1970)	0.57***	1.08***	2.21***
	(19.64)	(26.11)	(25.22)
Constant	4.38***	3.06***	6.23***
	(26.89)	(13.15)	(12.67)
Obs.	736	736	736
R^2	0.34	0.48	0.46

Notes: The dependent variable is investment in computer capital per worker in USD. Column (1) show ICT investment in 1982, column (2) for 1992, and column (3) for 1997. Columns (1) to (3) regress ICT investment per worker on log density in 1970. The coefficients are equal to the slope of the fitted line in Figure 2.7. Observations are weighted by population share in 1970. t-statistics are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Figure 2.E1: Density and Housing Values



(a) Rents 1980 (b) Rents 1990 (c) Rents 2000

The scatter plots show the correlations between historical levels of density (expressed by its log) and housing values in various years on the commuting-zone level. As expected from the model, the slope is positive. Observations are weighted by their 1980 population share.

Table 2.E2: Correlations of Density and Educational Polarization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1980 Median = 6	1980 Median = 7	1990 Median = 6	1990 Median = 7	2000 Median = 6	2000 Median = 7	2010 Median = 6	2010 Median = 7	2018 Median = 6	2018 Median = 7
Log Density (1970)	0.29***	0.27***	0.02	0.47***	0.42***	0.56***	0.07**	0.48***	0.08**	0.30***
	(12.56)	(10.00)	(0.49)	(15.08)	(13.64)	(16.42)	(2.07)	(19.34)	(2.32)	(10.94)
Constant	-0.95***	0.23	-0.26**	-1.06***	-1.37***	-1.34***	-0.51***	-1.36***	-0.81***	-0.62***
	(-8.56)	(1.46)	(-2.13)	(-6.31)	(-10.57)	(-7.07)	(-4.16)	(-10.35)	(-6.60)	(-5.13)
Obs.	658	77	439	297	507	229	342	393	263	382
R^2	0.19	0.57	0.00	0.44	0.27	0.54	0.01	0.49	0.02	0.24

Notes: The dependent variable is the Allison-Foster index of educational polarization. It is computed with Decennial Censuses on the commuting zone level. The table regresses the indices of all decades from 1980 to 2018 on log density in 1970. In all decades, the table distinguishes between commuting zones with median equal to 6 or 7, i.e. high school graduate or one year of college, respectively. Observations are weighted by population share in 1970. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table 2.E3: Parental Transfers to Children with six occupational groups (1988)

Occupational Group	(1) Parental Income	(2) Money from Parents (USD)	(3) Money from Parents (%)	(4) Time Help from Parents
Service	35936.69	217.96	.49	178.33
Transport/Construct/Mechanic	54574.99	264.13	.49	133.88
Cleric/Retail	55876.16	509.36	.95	78.64
Operators	54598.2	586.7	.93	137.07
Production/Craft	69030.2	436.3	.62	61.37
Managers/Professionals	79792.84	600	.79	73.01

Notes: This table shows parental income and transfers of time and money to their children. It shows that income is rising with occupational group, and so are monetary transfers by parents, both in absolute and percent. Help in terms of hours declines with occupational groups. The data is taken from the in 1988 by the PSID.

Table 2.E4: Parental Transfers to Children with six occupational groups (2013)

Occupational Group	(1) Parental Income	(2) Money from Parents (USD)	(3) Money from Parents (%)	(4) Support School (%)	(5) Time Help from Parents
Service	39757.98	78.59	.2	12.56	58.6
Transport/Construct/Mechanic	62125.93	613.63	.89	16.2	78.36
Cleric/Retail	67713.45	659.89	1.08	23.87	84.53
Operators	55508.43	389.71	.71	13.84	79.95
Production/Craft	69596.14	298.37	.39	21.35	74.5
Managers/Professionals	90523.03	1036.99	1.07	34.56	87

Notes: This table shows parental income and transfers of time and money to their children. It shows that income is rising with occupational group, and so are monetary transfers by parents, both in absolute and percent. Help in terms of hours declines with occupational groups. The data is taken from the in 2013 by the PSID.

Chapter 3

Firm-specific pay premiums and the gender wage gap in 21 European countries[1]

3.1 Introduction

Despite strong convergence in the gender pay gap, defined as the gap in hourly wages between men and women with similar observable characteristics, in developed countries over the last decades, a persistent gap remains, see e.g. Blau and Kahn (2017) and Kunze (2018). The gender wage gap remains a pressing policy issue given that labor market participation rates have mostly converged already. The current crisis with the spread of Covid-19 renews the attention to gender gaps as it impacts women disproportionately relative to men. Alon et al. (2020) summarize the various dimensions through which the crisis affects women.

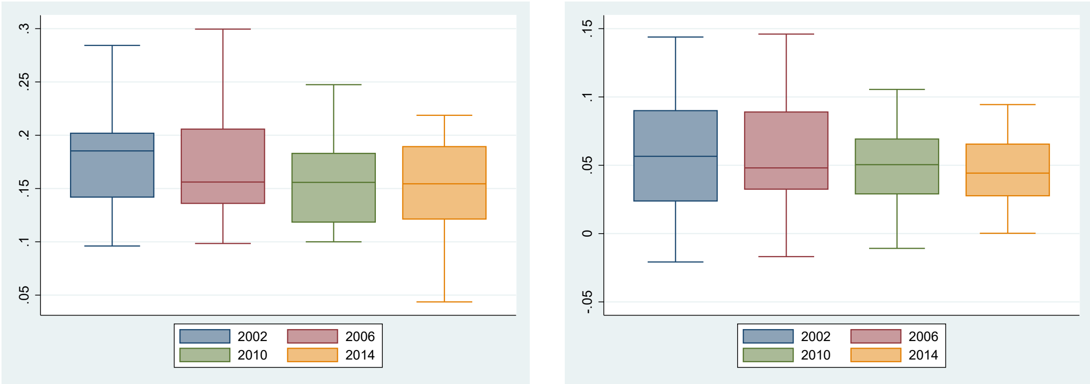
The left panel in Figure 3.1 shows the decline in the gender wage gap for the 21 European countries subject of our analysis between 2002 and 2014. In 2002, the average pay gap between men and women was 20%, and since then it has been falling by about one percentage point every four years, indicative of the slow progress during the last two decades. We focus on firm premia as an important determinant for the gender wage gap as it has been associated with overall wage inequality, e.g. for the United States by Song et al. (2019). On average, firm-specific pay differentials account for 35 to 39 percent of the gender wage gap, with strong country heterogeneity. For example, in 2014 the relative contribution of firm premia to the gender wage gap was the lowest in France with 11%, while it was the highest in Hungary with 77%.

Our first contribution is to disentangle the gender wage gap into a within- and between-component for 21 European countries over 12 years using a matched employer-employee data set. Previous studies, e.g. Card et al. (2016) and Coudin et al. (2018) investigate a single country, namely Portugal and France, respectively.[2] The authors use matched employer-employee data and estimate two-way fixed effects for firms and workers. For the identification of the fixed effects, both studies rely on worker moves across

[1] This paper is co-authored with Balazs Stadler (OECD).

[2] These studies call the within-firm component the "bargaining" channel, and the between-firm component the "sorting" channel.

Figure 3.1: Evolution of Firm's Contribution to the Gender Wage Gap



(a) Residual Gender Wage Gap (b) Total Contribution of Firm Components

The box plots show the absolute contribution of each component to the gender wage gap due to differential firm premia by gender for every year the SES was conducted. The left panel shows the wage gap that cannot be explained by observables, and the right panel presents absolute contribution of firms to the wage gap. The underlying country-specific results are shown in Columns (1) and (4), respectively, in Tables C2 to C5. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

firms. However, this requirement can induce a bias if the movers are not representative of the overall workforce or, as Andrews et al. (2008) argue, if the number of movers is low. This bias is empirically confirmed for various countries by Bonhomme et al. (2020). While we use four different survey waves, we cannot estimate worker-fixed effects due to the rotating nature of the survey, i.e. the firms we observe change between waves.

We exploit four waves between 2002 and 2014 of the "Structure of Earnings Survey" (SES) provided by Eurostat. The SES is a matched employer-employee data set, which provides harmonized and accurate data across all countries in the sample with a special focus on hourly wages. It contains detailed information on the relationships between the level of remuneration, individual characteristics of employees and those of their employer. We also explore heterogeneity of each component with respect to education and age. To our knowledge, we are the first to exploit this data set for a decomposition of the gender pay gap into a within- and between-firm component based on firm premia. Boll and Lagemann (2019) use the 2014 survey to decompose the gender wage gap into observables and unobservables, and to investigate the relative importance of observable characteristics to the pay gap.

The second contribution is to systematically investigate each component of the firms' contribution to the gender wage gap by relating each to different institutional settings. Specifically, we exploit firm-level variation of the collective bargaining regime and explore its relationship with the within-firm component, i.e. the firm-specific pay differential between men and women. We choose to investigate the role of firm-specific wage setting for the gender wage gap as Card et al. (2018) document that it is an important determinant for wage inequality. Next, we study the role of various family policies, such as social spending on families, parental leave and enrolment rates of young children in pre-education facilities, to the between-firm component. We focus on family-related policies as Barth et al. (2017) suggest that the between-firm component is largely due to married workers, i.e. it occurs around family formation, while Coudin et al. (2018) show that the between-firm component is surging after women give birth to their first child. As we explain below, this component is measured - by definition - on a more aggregated level. Therefore, we determine how these family policies affect the between-firm component for the full sample and by age group.

We put an emphasis on the gender wage gap and the contribution of firm premia to it across the life cycle. Our decomposition into the the within- and between-firm component is linked to three widespread explanations of the gender wage gap across the life cycle. The first explanation relates to non-pecuniary remuneration, i.e. women exchange higher-paying job for more family-friendly jobs in order to attain a career and a family. Hotz et al. (2017) provide evidence for this pattern of job changes after motherhood. Further, Lowen and Sicilian (2009) show that women receive family-friendly fringe benefits. If only non-pecuniary remuneration for women matters, then we would see a rise in the gender wage gap directly after motherhood, but it then stays constant over time. As it is related to job changes, we associate this explanation with a rise in the between-firm component around parenthood. The one-off increase can be stronger or weaker dependent on the availability of family-friendly workplaces.

The second explanation about the evolution of the gender wage gap across the life cycle relates to human capital depreciation. Angelov et al. (2016) provide evidence that women do not suffer strong immediate human capital depreciation, but wage trajectories over the lifetime differ strongly. Hence, breaks in employment around motherhood leads to a loss in human capital, which starts slowly, but accumulates over the life cycle. A similar argumentation resulting in the same pattern across life relates to losses in experience, as documented by Olivetti (2006). Similar to non-pecuniary remuneration, we associate the depreciation of human capital to the between-firm component because it is often induced by a break and limited policies to grant job protection.

The third and final explanation relates to discrimination based on the seminal work by Becker (1957) and the subsequent literature. In this case, the gender wage exists from the start and stays unchanged over the working life. We tend to relate this explanation to the within-firm component because then women should earn less than men independent of where they are working. With the within-firm component, discrimination could also relate to differences in bargaining: Babcock et al. (2003) show that female graduate students bargain much less than their male counterparts do, and Säve-Söderbergh (2009) provides evidence that women ask for lower wages in a field experiment. Discrimination as we define it, could also relate to inefficient allocation across sectors and occupations (Blau and Kahn, 2017) or to preferences (Gelblum, 2020). The latter two explanations are associated with the between-firm component, but independent of the underlying reasons, the gender gap stays unchanged across the life cycle with this explanation.

Our decomposition results of firm premia indicate that, on average, the within-firm and between-firm component are equally important in the set of countries subject to investigation. In other words, each component is responsible for around 50% of the overall contribution of firms to the gender wage gap for the full sample. Due to the normalization of our estimated firm-fixed effects based on Card et al. (2016), the within-firm component constitutes a lower-bound estimate. Comparing the development of each component over the four waves, i.e. between 2002 and 2004, we observe a decline in the average within-firm component, but not in the between-firm component. Given the documented decline of the gender pay gap and the firms' contribution due it in Figure 3.1, this finding implies that its decrease is entirely driven by the within-firm component.

Our heterogeneity analysis with respect to demographic characteristics such as age and education reveals further interesting insights. The decline of the within-component is largely shared across most demographic groups, i.e. it is independent of the level of education and affected workers across the whole life-cycle. A notable exception relates to workers with tertiary education, which we relate to the glass ceiling for women, as discussed e.g. by Christofides et al. (2013) for Europe. The between-firm component, however, varies strongly in their levels, and sometimes in their development over time, across demographic subgroups. The between-firm component rises strongly with age, and makes a jump between the first two age groups, i.e. between 20 to 29 and 30 to 39. This coincides largely with the age when women in Europe are giving birth to their first child, and this component tends to further increase at later stages in life.

Our analysis of the within-firm gender pay gap with firm observables puts an emphasis on the collective bargaining regime. We find negative correlations between the level of centralized wage bargaining and the within-firm wage gap, specifically relative to national bargaining. Two explanations could be responsible for this. First, the decline in collective bargaining in recent decades had a larger adverse impact on men than on women. The argument is analogous to Even and Macpherson (1993), who show that the decline of unionism affected men disproportionately and contributed to the falling gender wage gap. Second, under centralized bargaining the gender wage gap rises along the distribution due to the difference between actual and negotiated wages, which is larger at the upper tail of the wage distribution, while this difference is less present with alternative collective bargaining regimes. As men are more likely to be present in this upper tail of the wage distribution due better access to management positions, i.e. women face a glass ceiling (Antonczyk et al., 2010; Christofides et al., 2013), central wage bargaining can have an adverse impact on the within-firm wage gap relative to other wage setting regimes.

As explained above, we find a strong increase in the between-firm component with age, in particular around family formation. Olivetti and Petrongolo (2017) assert that family policy tries to guarantee women to combine a career and a family. However, family policy is very complex and its effects on labor market outcomes depend on many details. Therefore, we focus on eight indicators of family policy on a national level and determine the association between these family policy indicators and the between-firm component. We pay attention to how these indicators relate to the between-firm component across different age groups in order to determine whether they impact all groups or specifically the ones after family formation. We find that expenditure on families in the form of services and child enrolment in pre-education programs leads to a decline in the between-firm component of the wage gap. Importantly, the effect only materializes after family formation and then peters out. On the other hand, and in line with previous research, we provide evidence that the length of maternity leave is associated with a higher wage gap for the same age group, while length of paternity leave tends to have the opposite effect.

The paper is structured as follows: Section 3.2 introduces the matched employer-employee data set and explains subsample selection. Section 3.3 explains the estimation of the firm-fixed effects, their normalization, the decomposition in to the within- and between-firm component, and how we relate each component to institutional settings. Section 3.4 presents the results. Section 3.5 concludes.

3.2 A European Matched Employer-Employee Data Set

3.2.1 Structure of Earnings Survey

The data set is a matched employer-employee data set, implying that we observe information on both the worker and the firm. The advantage of the Structure of Earnings Survey (SES) is that it contains information on both sides of a match in the labor market for the majority of European countries.[3] Further, the information, in particular for earnings, which we are mainly interested in for estimating the gender wage gap, are harmonized across all countries. The SES takes place every four years, and we use the waves from 2002 until 2014. Within a year, the majority of countries conduct the survey in the month of October because it is considered the most representative as it is least affected by absences due to annual leave or public holidays. The SES collects the data in a two-stage procedure: First, a sample of local units is drawn, and second a random sample of employees is drawn from the chosen local units. Only local units of enterprises with more than 10 employees are drawn.

Crucial to our analysis will be (log) earnings per hour, and while it is included in the survey, we conduct two main changes to it. First, earnings in the SES are measured in domestic currency. In order to obtain comparable estimates (and hence firm-fixed effects) across countries, we measure earnings in Euro and apply the average exchange rate in

[3] It covers both member countries and candidate countries of the European Union. For a complete list, see Table A1 in Appendix A.

the respective year of the month of October available from the European Central Bank. Further, we also account for inflation and measure hourly wages in their 2014 values with inflation data from Eurostat. This also serves the comparability of the estimates, in particular of the wage equation, over time. Second, we incorporate annual bonuses in the earnings per hour as they constitute a rising fraction of remuneration, especially in high-paying jobs.

The SES also provides information on companies, specifically on firm size, the level of collective bargaining agreement and the form of economic control. With respect to firm size, we aggregate the information into three different categories in order to guarantee comparability across countries and years. The first category contains enterprises between 10 and 49 employees, the second category encompasses firms employing between 50 and 249 employees, and the third and last categories includes firms with more than 250 employees. The collective bargaining agreement is measured in seven categories, ranging from national level agreements to no agreement at all. Intermediate steps include industry-specific of firm-specific collective bargaining agreements. The form of economic control differentiates between private and public.

On the worker side, we explicitly use information on sex, age and education levels provided by the SES. One drawback of the SES is that both age and education are grouped into categories instead of providing detailed information, namely age into five and education into three categories.[4] The five age bands span from 20-29, 30-39, 40-49, 50 to 59, and 60 to 64. With respect to education, we differentiate between primary, secondary and tertiary education. We use the education and age categories for the estimation of firm premia and differentiate between the groups of each variable in our decomposition. For the former, i.e. the estimation of firm premia, we also exploit information on tenure as this is the closest variable to experience in our data set.

3.2.2 Subsample Selection

From the overall sample, we restrict our sample for the subsequent analysis. First, we exclude non-market services such as health and education. This leaves us with eight sectors which cover the whole economy, ranging from manufacturing and construction to various service sectors. Second, we drop skilled agricultural workers as the SES also does not include information on the agricultural sector. These workers are likely employed by other firms for upkeeping firm premises. Third, we omit workers below the age of 20 as countries differ slightly on the age of the lower-bound of the age band. Further, we do not believe that this age band contains valuable information on firm premia and their impact on the gender wage gap, most employees are likely to still be in education or vocational

[4] Technically, the SES includes more information on education for some countries in some survey years, but we group them into three groups for comparability across survey years.

training. Last, we exclude outliers in the hourly wage distribution, i.e. we drop the lowest and the highest percentile for each country and year.

Now, we turn to the necessary data requirements for the estimation of the gender-specific firm premia. Their estimation then allows us to compute the firms' contribution to the gender wage gap and to conduct both the decomposition and subsequent analysis of the premia, the within-firm and between-firm gender wage gap. The main requirement to obtain the firm-fixed effect for each gender is to observe firms which employ at least one man and one woman. To be precise, we need to see at least one man and one woman working for the same employer in the data. We might observe only employees of one sex in a firm, especially if it is small, as the employees in the SES are randomly sampled in the second stage of the sampling design explained above. In other words, the presence of single-gender firms constitutes a problem for assessing the role of firm premia in the gender wage gap, since we cannot observe the wages that would be paid to the opposite gender in a single-gender firm.

In our baseline analysis, i.e. the estimation of firm-fixed effects, decomposition and analysis of the firm premia, we use firms where we observe at least one man and one woman. This choice maximizes the number of firms we include in our sample. However, the main threat to properly estimate the firm-fixed effects, which we use in the decomposition and the subsequent analysis, is that it may include worker-specific unobservables instead of the firm premium. In order to mitigate this threat to precisely estimating firm premia, we conduct the same analysis with a subsample, where we require to observe at least five men and five women per firm. Clearly, this choice comes at the expense of the number of firms, in particular small firms.

Tables A2 to A5 in Appendix A show how employer-related variables change for the years 2002 to 2014 with the different requirement to observing a minimum amount of employees of each sex. Column (1) always shows the sample statistics without the requirement to observe at least one employee of each gender, but includes the sample restrictions mentioned above, while columns (2) and (3) require to observe at least 1 and 5 employees of each gender, respectively. The composition of firm size exhibits the most pronounced change over the three samples and it holds in all years to a more or less strong degree. Specifically, small firms with 10 to 49 employees fall out of the baseline sample, i.e. when we require to observe at least one male and one female employee. For example in 2002, small firms make up nearly 47% of total firms in the data set without any restrictions, it drops to close to 45% for the baseline sample, and to nearly 28% when requiring to observe at least five employees of each sex. This in turns implies that the share of medium-sized and large firms - i.e. enterprises employing between 50 and 249 workers, and more than 250 workers, respectively - increases with these samples. On average, the share of firms under public controls rises with data requirements.

Further changes in firm-related observables with data requirements affect the sector of economic activity and the level of collective bargaining. The largest three sectors in all years are manufacturing, wholesale and retail, and real estate and business activities. When comparing the shares over the years, manufacturing shows a continuous decline over the years as shown in previous research, whereas the real estate and business activities rises and even overtakes manufacturing in 2010.[5] With the data restrictions, especially the share of manufacturing rises, whereas the shares of both construction and wholesale and retail fall. This is probably related strongly to the previously mentioned change in firm size, as firms in the sectors with falling shares are typically small. With respect to the level of collective bargaining, there is no clear-cut pattern over all years. In some years, the share of firms operating under national agreements rises, whereas it falls for firms without any collective bargaining agreements. A similar movement can be observed for industry and enterprise agreements. However, in some years the data requirements lead to changes in the opposite direction, hence there is no regular pattern with respect to collective bargaining dependent on sample selection.

The data requirements do not only lead to changing firm characteristics, but they also imply changes in employee-related observables. Tables A6 to A9 in Appendix 3.1 present these changes. In the tables, we differentiate between male and female employees, similar to Card et al. (2016) and Coudin et al. (2018). Specifically, the tables present changes in log hourly wage, share of each education and age group, the share of each occupation at the ISCO one-digit level, and the shares of both part-time workers and temporary contracts. The share of age groups, does not change significantly with the data requirements, neither for men nor for women in any survey year. Similarly, the share of occupations also exhibits hardly differences over the different samples in any given year. This is interesting given that the share of sectors of activity changes as described above. It indicates that workers of all broad occupations are necessary in broad sectors of activity. Further, part-time and temporary work do not change much due to data requirements.

The main adjustments of employee-specific observables relate to education and hourly wage. With respect to education, the more demanding the data requirements, the stronger the fall in workers with primary education. Simultaneously the share of workers with secondary and tertiary education the in every survey year, and this holds especially for the latter with stronger data requirements. This is in line with the observation, e.g. Oi and Idson (1999), that large firms employ more educated workers. These changes in educational composition of the samples can also explain the rise of (log) hourly wage observed when making the data requirements.[6] However, it is important for our analysis that these changes both genders equally, which is the case in all survey years.

Taking into consideration the changes described above, we use the data set with one em-

[5] Real estate and business activities is a very broad sector in NACE Rev.1, and actually constitutes the sector which is most split up with in the NACE Rev.2 classification with three sectors therein.

[6] One exception is for the survey in 2006, where (log) hourly wages are nearly unchanged, and even drop slightly. The same holds for the share of workers with tertiary education.

ployee of each sex in our baseline analysis. We do so because its differences to the full sample are typically smaller than for the sample with five employees of each sex. This choice comes at the expense of not estimating the true firm premia for small firms, and thus misreporting the gender wage gap in these firms. This holds true if the residuals in our wage equation also captures worker-specific unobservables. To encounter this threat, we also conduct the whole analysis with the subsample which only includes at least five male and female employees in a sensitivity analysis. The baseline sample includes 582,340 firms with more than 19.2 million employees across all four survey waves, whereas the subsample for the robustness analysis consists of 193,286 enterprises with more than 15.3 million workers.

3.3 Methodology

This section presents every step of the estimations in detail using the matched employer-employee data set described previously. Generally, we care about the firms' contribution to the gender wage gap. Overall, there is growing evidence of the firm's role in overall inequality as argued by Song et al. (2019). Further, two recent single-country studies suggest firm premia play a role for pay differentials between men and women. Card et al. (2016) are the first to compute the firm's contribution to the gender wage gap based on firm pay differentials and to decompose it using employer-employee matched data for Portugal. Coudin et al. (2018) conduct the same analysis for France, and relate observed gaps to firm-specific components over the life-cycle.

We first explain how we estimate the firm-fixed effects. We conduct the estimation of firm premia in two steps because we assume gender-neutral returns to observables such as education, age and tenure. The next step comprises the decomposition of the gender wage gap into a between- and within-firm component following Card et al. (2016). We will conduct this exercise for the baseline sample and for various subgroups based on education and age. After the decomposition, we present a regression framework, which allows us to link firm observables and workforce composition to both the average firm premium and the within-firm gender wage gap. Finally, we estimate correlations between various indicators relating to family policy and the between-firm gender pay gap.

3.3.1 Discussion

Adequately estimating the firm wage premia is still an unsolved problem of the field, with several competing approaches. The seminal paper is, of course, Abowd et al. (1999), which introduced the multi-way fixed effects estimation. The authors included worker and firm fixed effects in a regression framework, capturing both the firm wage premia and the unobserved earnings characteristics of workers. A frequent criticism of this approach is that the worker fixed effects are identified by job-to-job mobility of workers. Frequent movers are likely to be different inherently than workers with low job mobility, thus the estimates will suffer from "limited mobility bias" (a version of the incidental parameter problem). This may explain why unobserved worker characteristics and firm wage premia is correlated negatively with this approach, e.g. Andrews et al. (2008). Borovičková and Shimer (2017) explicitly addresses this problem by comparing the workers' average residual wage (over the job spells in other firms) with the average wage of co-workers in the firm (leaving the worker herself out of the calculation).

Bonhomme et al. (2017) address the limited mobility bias by grouping firms together, thus generating "artificial" mobility to identify the model. Simulations have shown the advantages of this approach (Bonhomme et al., 2020). Barth et al. (2016) suggest another approach, the authors examine the role of establishments play in wage inequalities with a decomposition and for to this end they augment the human capital equation with an establishment fixed effects, effectively assuming that the workers variables capture all of the relevant worker characteristics. This approach demands less of the data, though it might overestimate the importance of firms, attributing some of the unobserved worker heterogeneity to firms. This approach has been effectively applied to the question of gender wage gap by Hara (2018). We will also rely on Barth et al. (2016), mainly because of data constraints. The SES is a pooled cross section, hence there is no possibility for us to control for worker unobservable characteristics.

We compare the estimated gender wage gap and its components for the decomposition method based on Card et al. (2016) with the estimation method using firm-fixed effects similar to Barth et al. (2016) and Hara (2018). Figure B1 in Appendix 3.2 shows that the residual gender wage gaps for all countries and years is essentially equivalent. The pattern is slightly more diluted than for the total gender wage gap, but both the within-firm components and the between-firm component take on very similar values and no obvious bias is visible from the data. Figure B2 compares the components of the gender wage gap across methods.

3.3.2 Estimating firm fixed effects

Our goal is to understand the role of firms for the gender wage gap, hence we abstract from employee-specific characters. Therefore, the first step is to estimate the firm fixed effects in a two-step procedure like Card et al. (2016) but for a different reason. The main reason is our assumption that returns to observables are equal across genders, whereas the authors assume gender-specific returns to observables based on an Oaxaca-Blinder decomposition. However, we are not interested in differences in returns to observables, and as Weichselbaumer and Winter-Ebmer (2005) show, the results of both estimations are equivalent. Hence, in the first step we determine the residual wage for every worker, i.e. the wage component which cannot be explained by observable worker characteristics. As we assume gender-neutral returns to observables we include all observations of both men and women in our baseline sample with at least one worker per gender as presented in Tables A6 to A9.

We focus on differences in the "residual wage gap", i.e. the component of wages, which cannot be explained by observable characteristics of employees. To do so, in a first step, we estimate a standard wage equation including worker-level characteristics. The vector of employee observables includes age (5 groups), education (3 groups), tenure and tenure squared. We estimate this wage equation separately by country and year as the returns to observable characteristic may differ across space and time. The wage equation takes on the following form:

$$log\ w_{ict} = \alpha_0 + \boldsymbol{X'}\Theta_{ct} + \varepsilon_{ict}, \tag{3.1}$$

where w_{ict} represents the log hourly wage per worker i in country c in survey year t. It is explained by the vector $\boldsymbol{X'}$ encompassing worker characteristics as described above. The residual ε_{ict} contains the unobservable wage component, which we are interested in to compute and decompose the gender pay gap. The equation also includes a constant α_0. Observations are weighted by their sample weights provided by the SES.

In the second step, we explain the residual wage component with firm-fixed effects for each gender separately. At this point, the assumption of exploiting only firms with at least one woman and one man turns out to be crucial. Technically, we could estimate a firm-fixed effect for single-gender firms, but we cannot use them in the subsequent decomposition and analysis because we cannot observe the firm premium of the opposite gender in a single-gender firm. Hence, we estimate the following equation for men and women separately using the baseline sample, and by country and year as before:

$$\widehat{\varepsilon^G_{ict}} = \psi^G_{0ct} + \psi^G_{jct} + \mu^G_{ict}, \quad \text{where} \quad G = \{M, F\} \tag{3.2}$$

where a firm-fixed effect (ψ^G_{jct}) of firm j and a constant (ψ^G_{0ct}) in country c at time t, both gender-specific due to the sample split, explain the residual wages of males (M) and females (F). The difference between the expected values of the gender-specific firm-fixed effects (plus the gender-specific constant) is equal to the unobservable gender wage gap observed in the data.

3.3.2.1 Normalization

Similar to Card et al. (2016) and Coudin et al. (2018) we also normalize our gender-specific firm-fixed effects because the wage premia are only identified relative to a reference firm. However, we do not possess data on firm characteristics outside the ones provided by the SES such as value added per worker or similar information regarding productivity and hence wage surpluses. For our baseline decomposition and estimations, we therefore use the hourly wages in the data for normalization. Implicitly, we assume that the lowest-paying firms also pay the lowest surpluses to their employees. To define a set of firms serving as a benchmark to normalize the firm-fixed effects, we exploit the definition of "low-pay" by the OECD. Low-pay indicates that a worker earns less than two-thirds of the median wage. We select a firm to pay no wage surpluses if the average payment to all employees is below two-thirds of the median wage in a given country in a given year. In a robustness analysis, we use all firms in the hotel and restaurant sector to serve as normalization. This decision is based on Card et al. (2016) and references therein.

3.3.3 Decomposition

Following Card et al. (2015), we decompose the firm-specific pay differentials into within- and between-firm components. We differ in the naming of the components, i.e. we call their bargaining and sorting effects the within-firm and between-firm component, respectively. Here, equation (3.2) provides the framework for a decomposition of the firm wage premiums based on Oaxaca (1973) and Fortin et al. (2011). This allows us to decompose the male and female firm-fixed effects into a combination of between- and within-firm component for every country in every survey year separately:

$$E\left[\psi^{M}_{jct}|male\right] - E\left[\psi^{F}_{jct}|female\right] = E\left[\psi^{M}_{jct} - \psi^{F}_{jct}|male\right] + E\left[\psi^{F}_{jct}|male\right] - E\left[\psi^{F}_{jct}|female\right] \tag{3.3}$$

$$= E\left[\psi^{M}_{jct} - \psi^{F}_{jct}|female\right] + E\left[\psi^{M}_{jct}|male\right] - E\left[\psi^{M}_{jct}|female\right], \tag{3.4}$$

where both equations (3.3) and (3.4) only differ in both their fixed effects and distribution by gender. In both equations, the first term equals the within-firm component, and the second term equals the between-component of the gender wage gap. In particular, the within-firm component reflects the average difference between men and women if they were working in equal proportions in the same firm. In equation (3.3) this effect is calculated across the distribution of jobs held by men, while it is the distribution of jobs held by women in equation (3.4). The between-firm component denotes differences in the average wage of women in equation (3.3) and of men in equation (3.4) attributable to differences in the distribution of men and women across firms, assuming they earn identical wages within firms.

It is important to note how normalization of firm premia affects both the within- and

between-firm component. The former changes with normalization, while the latter is independent of any normalization. This is because - in order to calculate the latter - the decomposition method uses the firm effects of only one gender, hence the normalization (with the same base) has no impact. On the other hand, to compute the within-firm component the method exploits the firm effects of both men and women, and hence normalization of each gender-specific firm effect matters. However, as Card et al. (2016) show, if the average of the firm-fixed effects for the female sample is smaller than for the male sample, then the within-firm component we obtain from our decomposition is an underestimate. Table C1 shows that this condition is met in all cases except two.[7] Without normalization of the firm-fixed effects, our within-firm component of the gender wage gap would be “inflated”. In particular, they would be equal to the difference between the residual wage gap and the between-firm component.
The decomposition method of Card et al. (2016) has the great advantage that we can measure gender wage gaps conditional on worker characteristics within a firm. With other methodologies, such as a shift-share analysis or following Barth et al. (2016), we could measure the within-firm component only on the national level. The former also allows to exploit the female versus the male distribution and thus allowing a higher comparability compared to the baseline decomposition, while the latter exploits the joint distribution of men and women.

3.3.4 Estimation strategy

We explain how we work with our estimates of both the within- and between-firm components. For the former we possess information on the firm-level and can link these to firm observables similar to Coudin et al. (2018). To be precise, we exploit the estimated firm premia (after normalization) and investigate how firm observables influence both the level of firm premia and the within-firm gender pay gap. The latter, by definition, is not available on the firm-level, therefore we resort to simple cross-country regressions using family policy indicators. We want to emphasize that we do not claim any causality for any of these estimates, we are showing (conditional) correlations of each component with potential factors influencing them. Specifically, we focus on institutional settings.

3.3.4.1 Within firms

Investigating factors impacting the within-firm gender wage gap, we directly use the gender-specific firm-fixed effects we estimated for men and women in equation (3.2). Specifically, we construct the difference firm-fixed effects between the male and female sample. One might think that we possess two different types of within-firm gender wage

[7] Specifically, these two cases are Hungary in 2002 and Sweden in 2010. When exploiting firms in the hotel and restaurant sector, there are also two exceptions.

gaps based on equations (3.3) and (3.4), but this is because we evaluate them at the national distribution of men and women separately. On the firm level, there is no scope for doing so.

In the first step of the estimation strategy, we investigate how the firm-level differences in gender-specific fixed effects are related to other observable firm characteristics available or computable from data in the SES. We conduct the same analysis exercise as Coudin et al. (2018, Table 8) and regress the within firm gender gap in firm-fixed effects on a vector firm observables. In particular, the observables we consider are collective bargaining, firm size, type of control, share of men, share of workers below low-pay, share of part-time workers, shares of various occupations and the share of female in the same occupations. In a regression framework, we are controlling for country-, time- and sector-fixed effects because we are not estimating this equation by country and year as we did with the wage regression and the estimation of firm-fixed effects above. The regression equation for the within-firm gender wage gap takes on the following forms:

$$\psi^{M}_{jct} - \psi^{F}_{jct} = \boldsymbol{Y'_{jct}}\Phi + \gamma_c + \gamma_t + \gamma_s + \zeta^{M}_{j} \tag{3.5}$$

where the left-hand side reflects the difference in normalized gender-specific fixed effects for firm j in country c at time t. As argued above, we obtain the gender-specific firm premia from equation (3.2. The vector $\boldsymbol{Y'_j}$ contains observed and computed firm-level characteristics described previously in this subsection. We include a battery of fixed effects in order to account for unobserved heterogeneity across time (γ_t), space (γ_c) and sector of activity (γ_s). Observations are weighted with the firm sample weights provided by the SES.

3.3.4.2 Between firms

The main concern with the between-firms component in a regression design is that we cannot measure it on the firm level. While an analysis on the sector or occupation level would be preferable, we would require information on job amenities in these sectors or occupations. Due to the lack of these information, we will estimate correlations exploiting variation across time and countries. The aggregation also implies that we can exploit both between-firm components based on equations (3.3) and (3.4). Due to the low number of observations on this level of aggregation, we will only include one indicator at a time. While we put no emphasis on the absolute size of the correlations, we will investigate the signs.

The regression of the between-firm component takes on the form:

$$Between^{G}_{ct} = \omega^{G} FamPolicy_{ct} + \gamma_t + \xi^{G}_{ct} \quad \text{where} \quad G = \{M, F\} \tag{3.6}$$

where the left-hand side reflects the between-firm component using the difference of either male or female effects of the gender wage gap in country c and year t. We regress the between-firm component on various indicators of family policy from the OECD data base relating to social spending, length of parental leave and enrolment rates. We include a year-fixed effect, hence our identification relies on within-period variation. We do not include country-fixed effects because of the limited sample and the large degree of variation they eliminate.

We estimate equation (3.6) for the full sample and by age group because we assume that family policy differs in their impact depending on family formation. As argued previously, the average woman in Europe gives birth to her first child at the age of 29, so we pay particular attention to the differences in the point estimates of ω^G between the age groups of 20 to 29 and 30 to 39. We also investigate all other categories of age in order to see whether the impact of family policy remains stable across age groups or potentially peters off. One issue with the estimates for older generations, in particular for the last two, i.e. from 50 to 59 and 60 to 65, is that the contemporaneous family policy probably differs from the family policy around the time of family formation of the older generation in the sample.

3.4 Results

We now discuss the findings based on the methodology outlined previously between 2002 and 2014 from the SES. We briefly outline the influence of observables on hourly wages and we document how firm observables such as collective bargaining regime, firm size, type of control and workforce composition variables with firm premia to lend credibility to our estimates. Then, we turn to our first main exercise, namely the decomposition of the firm-specific pay differential between men and women. We break down the firms' contribution to the gender wage gap into its within- and between-firm component and document changes over time for the full sample and various subgroups. Specifically, we differentiate by age to investigate change of both components over the life-cycle, and by education to see whether the overall decline in the wage gap is shared across all groups. Our second main exercise relate different institutional settings with each component. We link wage setting institutions on the firm level to the within-firm gender wage gap, and we explore the impact of family policies on the between-firm component on the country level. We put a special focus on differences across age groups for family policy.

3.4.1 Mincer equation

The first step is to determine residual wages by regressing log hourly wages on observable worker characteristics shown in equation (3.1). One drawback of the SES is the coarse and limited information on these characteristics, i.e. age and education are categorical variables and hence point estimates for both observables are relative to a baseline category. For the former, this is the age group from 20 to 29, and for the latter these are workers with primary education. We estimate the regression equation for every country and every year individually to account for variation in returns to all observables. We then compute the mean of the estimation parameters by year to show how they change (on average) over time.

Table 3.1 shows the mean coefficients for the four different waves. Relative to the baseline category for education, i.e. primary education, the average returns to secondary and tertiary education are falling over time. However, the decline in average returns to secondary education in percentage points is substantially stronger compared to tertiary education, namely 14% to 8.3%. This observation is likely due to the observed polarization of labor markets across Europe shown by Goos et al. (2014).[8] The returns to age relative to the baseline category are moving in opposite directions. For example, returns to the age group 30-39 are largely unchanged across the four waves of the survey, while the returns to other age groups tend to fall. One notable exception is the significant rise in average returns to being 30 to 39 between 2010 and 2014. Overall, the life cycle pattern established in the literature, specifically an inverse U-shaped pattern, is visible across all four survey years in the returns to age groups.

Table 3.1: Returns to worker characteristics for subsample of firms with at least 1 employee of each gender

	(1) 2002	(2) 2006	(3) 2010	(4) 2014
Secondary education	0.178	0.167	0.163	0.160
Tertiary education	0.612	0.590	0.604	0.574
Age 30-39	0.132	0.126	0.125	0.133
Age 40-49	0.154	0.137	0.135	0.159
Age 50-59	0.153	0.144	0.116	0.133
Age 60-65	0.131	0.125	0.112	0.109
Tenure	0.031	0.033	0.028	0.024
Tenure^2	-0.001	-0.001	-0.000	-0.000
Constant	1.779	1.820	2.000	1.630

Notes: The table shows the means obtained from the Mincer wage regression in equation 3.1 for all years. The average returns to each characteristics is based on the country-specific estimations as every country might exhibit different returns to worker characteristics. Primary education and age group 20 to 29 constitute the reference group for each. Tenure is a continuous variable. The sample on which we estimate the returns to worker characteristics includes one men and women per firm. A large majority of the country-specific estimates are statistically significant on conventional levels.

Equipped with the residual wages, i.e. the wages that cannot be explained by the observables included in Table 3.1, we determine gender-specific firm premia. To do so,

[8] While the authors focus on employment polarization, other studies, e.g. David and Dorn (2013) have shown that polarization also occurs in terms of wages in the United States.

we regress the residuals on firm-fixed effects for the samples including either only male or female workers. We then normalize the fixed effects by firms, where the average wage is below paying the definition of low-pay by the OECD, i.e. below two-thirds of the median pay, in a given country and year. As argued above, this normalization leads to a lower-bound estimate of the within-firm component, while the between-firm component is completely unaffected by normalization. The next step comprises of the decomposition of the normalized fixed effects into their within- and between-firm components. We obtain lower-bound estimates of the within-firm component because the fixed effects for women are lower in the firms paying below low-pay then those for men.

3.4.2 Firm Premia and Firm Characteristics

The credibility of our estimated firm premia (after normalization) is crucial to our decomposition. Therefore, we now turn to the analysis of the estimated firm-fixed effects, and relate them to firm observables. The analysis is very similar to the one of the within-firm pay differential in premia as described above, and presented in equation (3.5). Instead of the within-firm wage gap on the left-hand side of the estimation equation, we have the weighted average firm premia. We weigh the firm premia by employment shares of men and women, i.e. we account for differences in workforce gender composition across firms. Due to the requirement to observe at least one employee of each gender, the weighted firm premia do not differ strongly from the unweighted firm premia. In fact, for the full sample including all years and countries, the correlation of weighted and unweighted firm premia exceeds .97.

Table 3.2 shows the results from the regressions, both for all years combined as well as for each year individually. Similar to the analysis for the within-firm wage gap below, we include the level of collective bargaining, firm size, type of control and workforce composition variables. Starting with the degree of centralization in the wage bargaining process, we remark that the national level serves as a benchmark for the other levels of pay agreement. The point estimates for most categories are positive and statistically significant and tend to rise for all over the waves of the SES. In fact, in 2002 the point estimates for all categories were negative and except for two cases statistically significant. This common trend seems to indicate a decrease of average firm premia over time for firms under a national collective bargaining regime. The question we cannot answer here how much is due to overall decrease in the centralization of collective bargaining and whether firms actively self-selected into less centralized bargaining regimes.

In line with findings established in the literature is that larger firms pay higher wages, our results indicate that larger firms pay higher premia relative to firms with less than 50 employees. However, these firm premia are declining over time, in particular for mid-sized firms with 50 to 249 employees, and to a lesser extent for very large firms with more than

Table 3.2: Average Firm Premia

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	0.069***	-0.013***	0.003	0.018***	0.083***
	(0.000)	(0.008)	(0.478)	(0.000)	(0.000)
Region-Industry Agreement	0.068***	-0.028***	-0.001	-0.048***	0.097***
	(0.000)	(0.000)	(0.845)	(0.000)	(0.000)
Enterprise agreement	0.063***	0.023***	0.004	0.041***	0.055***
	(0.000)	(0.000)	(0.397)	(0.000)	(0.000)
Local Unit Agreement	0.039***	-0.032**	-0.021***	-0.015	0.013
	(0.000)	(0.021)	(0.000)	(0.255)	(0.557)
Other agreement	0.017***	-0.015**	-0.058***	0.005	0.062***
	(0.001)	(0.042)	(0.000)	(0.618)	(0.001)
No agreement	0.102***	-0.003	0.033***	0.060***	0.064***
	(0.000)	(0.482)	(0.000)	(0.000)	(0.000)
Firm Size					
50-249 Employees	0.020***	0.043***	0.039***	0.022***	0.030***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
250+ Employees	0.026***	0.048***	0.037***	0.050***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control					
Private	0.083***	0.022***	0.031***	0.086***	0.087***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	0.002***	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.003***	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clerks (%)	0.000***	0.000***	-0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.213)	(0.000)	(0.000)
Female among Executives (%)	-0.000***	0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among White Collars (%)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Female among Clerks (%)	0.000***	-0.000	0.000***	0.000	0.000***
	(0.000)	(0.554)	(0.000)	(0.192)	(0.000)
Female among Blue Collars (%)	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%)	-0.006***	-0.005***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%F-%M)	-0.000***	-0.000***	0.000	-0.000***	-0.000***
	(0.000)	(0.001)	(0.504)	(0.000)	(0.000)
Observations	413035	70918	118750	95955	127412
R^2	0.55	0.47	0.48	0.59	0.55

Notes: The dependent variable is the average firm premia (weighted by employment shares) based on estimated firm-fixed effects for each gender. The firm premia are normalized by low-pay firms. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

250 employees. For the latter, there is rise in firm premia in the 2010 survey, which can be due to the Great Financial Recession. Overall, this decline in the large firm premium is consistent with the results by Bloom et al. (2018), who show a decline in the large-firm wage premium for the United States. Firm premia in privately controlled firms are larger relative to firms under public control. Balcik et al. (2010) argue that public companies also have non-monetary performance requirements, hence the finding of lower wage premia are not surprising and in line with previous literature.

Last, we investigate the relationship between weighted firm wage premia with workforce composition variables based on Coudin et al. (2018). Most importantly, the share of managers is positively associated with firm premia, while the share of employees earning below low-pay is negatively associated. This in line with the authors' findings for France, albeit our coefficients are much smaller. Importantly, the coefficients are very stable across all five specifications. All other workforce composition variables, including shares of occupational groups, are all essentially equal to zero.

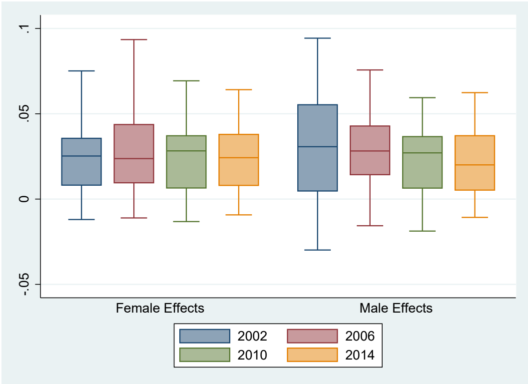
3.4.3 Decomposition

We decompose the gender pay differential based on the methodology by Card et al. (2016) using firm premia into a within-and between-firm component. The main focus of this section is to investigate how both the within- and between-firm components change over the four different waves of the SES, i.e. between 2002 and 2014. We pay attention to differences across subgroups, in particular with respect to age and education. The former is particularly important to assess which components matters for the life cycle pattern of the gender wage gap. We will make use of box plots to show how the components differ across the survey years, but for a clearer analysis of the components over the life-cycle, we make use of the latest survey to our availability in 2014 and examine how the components change across the life cycle.

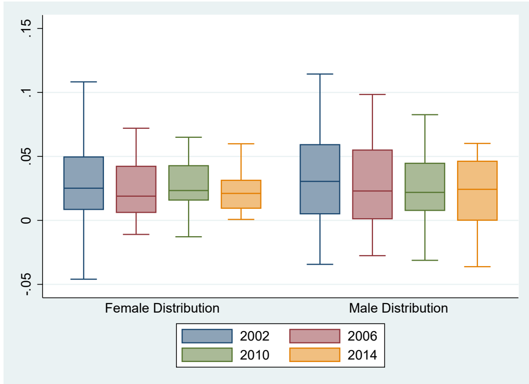
3.4.3.1 Full sample

In Figure 3.1 we already outline that both the residual wage gap and the firms' contribution to it are falling. The naturally occurring question is now to determine which component is responsible for the decline, or whether both contributed to it between 2002 and 2014. Figure 3.2 shows the box plots of how the two components change over time. The left panel shows the between-firm component using either female or male effects, while the right panel shows the within-firm component using either the female or male distribution. Whenever discussing the components, it is important to keep in mind equations (3.3) and (3.4). The equations indicate that the sum of the between-firm component using female effects and the within-firm component using the male distribution is equal to the firms' contribution to the gender wage gap, which is also equivalent to the between-firm component using male effects and the within-firm component using the female distribution.

Figure 3.2: Contribution of Components



(a) Between-firm component



(b) Within-firm component

The box plots show the absolute contribution of each component to the gender wage gap due to differential firm premia by gender for every year the SES was conducted. The left panel shows the between-firm component, estimated with either female or male effects. The right panel presents the within-firm component, estimated with either the female or male distribution. The results by country are shown in Columns (4) to (7) in Tables C2 to C5. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

Figure 3.2 gives two important insights as to why the decomposition of the firms' contribution to the gender wage gap matters. First, it shows the importance of each component to the firms' contribution to the gender wage gap. Both components are nearly equally important over all years, independent of whether we consider male or female effects for the between-component, or female and male distributions for the within-component. Second, the between-firm component with female effects is largely unchanged, while there is a modest decline when computed with male effects. On the other hand, the within-firm component declines for both components, albeit it is stronger for the male distribution. As Card et al. (2016) argue, if the within-firm component using the female distribution is larger than when using the male distribution, this indicates that men are more concentrated where the gap in firm premia is smaller. Hence, our results indicate that men are increasingly concentrated in firms with low pay premium gaps.
Our results resemble those of single-country studies, i.e. for Portugal and France, for which Card et al. (2016) and Coudin et al. (2018), respectively. The former look at the period 2002 to 2009, while the latter consider the period 1995 to 2014. In both countries, the respective authors find that the between-firm component, i.e. in their words the sorting channel, is more important than the within-firm component. Our findings replicate the differential importance for the components in both countries. Further, taking the averages for Portugal from 2002, 2006 and 2010, our results equal those of Card et al. (2016) quite closely also in magnitude. Comparing our findings for France with those of Coudin et al. (2018), the within-firm component is negative in the single-country study, our results are

only negative when using the female distribution. However, exploiting this distribution the within-component is larger in magnitude than with the male distribution.[9]
The box plots in the previous figure hide a lot of cross-country heterogeneity, especially with respect to changes over time. Tables C2 to C5 in Appendix 3.3 provide a better overview. Examples for opposite movements for the between-firm component are Italy, Slovak Republic, and the Netherlands and Norway. While the former two experience declines in both between-firm components, the latter two see a rise in the same component. Overall, as argued above, these country-specific changes seem to cancel each other out, especially when exploiting female effects. While the average within-firm component of the gender pay gap declines over time, the box plots also hide substantial heterogeneity here. For example, between 2002 and 2014 this component falls in Belgium, Spain and Sweden, but increases in Germany, France and Portugal.

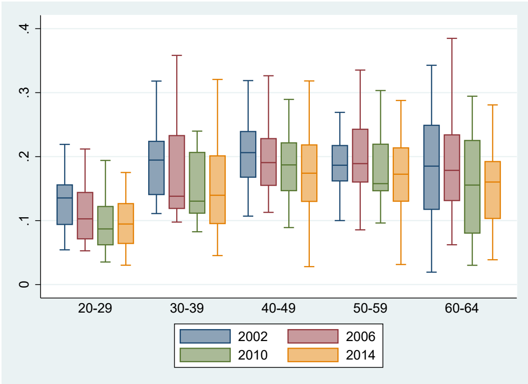
3.4.3.2 Age

We now turn the analysis of subgroups, starting with age. It is established in the literature, e.g. Blundell et al. (2016), Kleven et al. (2019a) and Kleven et al. (2019b), that the overall wage gap is rising with age, which is particularly linked to the incidence of motherhood. While we do not have any information on family status or parenthood, the average age of women giving birth to their first child is around 30 in many European countries.[10] Luckily, the SES contains a break between two age groups at the same age, which we will tentatively exploit as the start of parenthood in our sample. We are aware that we do not get specific results with respect to motherhood, but it allows us to look how the different components change over the life cycle and how motherhood likely affects each of them.

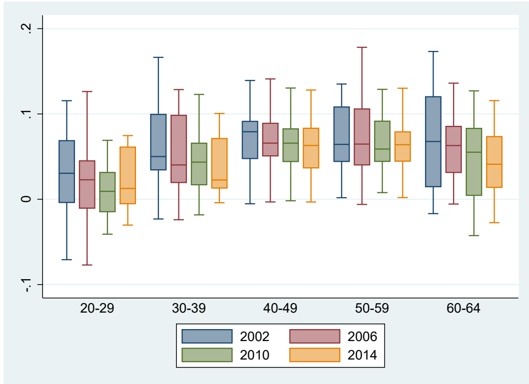
In line with the previous literature, the left panel of Figure 3.3 shows the well-known life-cycle dimension of the gender wage gap, namely an inverse U-shape. The sharpest increase, however, occurs between the age categories 20 to 29 and 30 to 39, which we associate with to motherhood. Further, the level of the residual wage gap has declined between 2002 and 2014 across all age groups, indicating that the progress in declining wage gaps has been shared across all age groups. One exception is the group of 40 to 49, where the gender wage gap has hardly changed over time. The right panel shows the contribution of firms to the gender wage gap by age group across the four waves of the SES. Both Card et al. (2016) and Coudin et al. (2018) find an increase in the contribution of firms over the life cycle in absolute terms, which we confirm on a European level. The jump between the first two age categories is also visible in this panel, and the subsequent age groups only recover weakly in terms of the firm's contribution. In other words, the inverse U-shape as in the left panel is much weaker in the right panel, in particular the

[9] We use the results for 2005-2014 in Table 9 in Coudin et al. (2018) because this time horizon coincides more with ours.
[10] In 2016, the European average was 29.

Figure 3.3: Evolution of Firm's Contribution to the Gender Wage Gap by Age



(a) Residual Gender Wage Gap



(b) Total Contribution of Firm Components

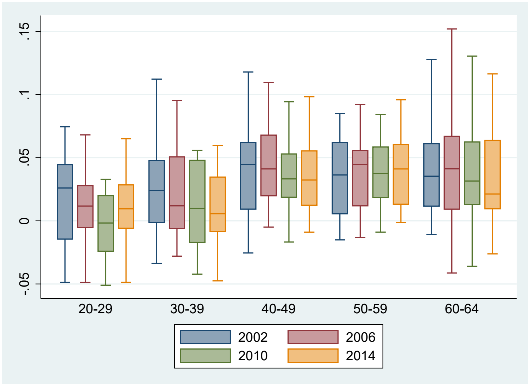
This figure shows the residual wage gap and the firms' contribution to the gender pay gap for five different age groups and across all waves of the SES. The results are based on the analysis explained in Section 3.3 for each age group. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

decline at later stage of the working life. This indicates a "scarring" effect of motherhood and that firms drive it overproportionally.

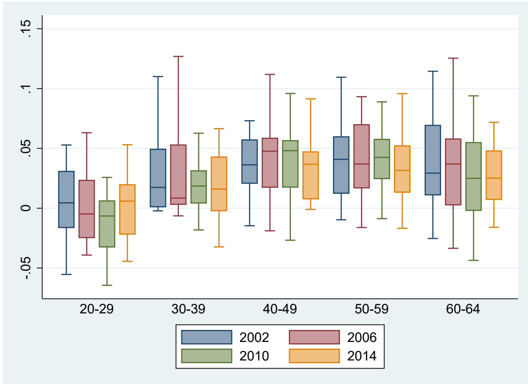
Figure 3.4 shows the evolution of both components with the analogous box plots as for the full sample. Based on equations (3.3) and (3.4), each panel depicts the components dependent on their way of computation. The upper two panels of the figure present the between-firm component, while the lower two panels depict the corresponding within-firm component. The upper two panels indicate a decline of the between-firm component between 2002 and 2014 for the youngest or youngest two age groups, depending on whether the component is calculated using female or male effects, respectively. This decline at the early stages of the working life can be explained with a reduction in discrimination of women when entering the labor market. Potentially, this can also be explained by changing initial preferences of women in terms of majors and occupational choice as Gelblum (2020) and Bertrand (2020) highlight.

The between-firm component does not change substantially in later stages of the life cycle. Instead, the jump between the age groups 30-39 and 40-49 for the between-firm component using male effects and between the age groups 20-29 and 30-39 when using female effects tends to increase over time. This jump in the gender wage gap and the between-firm component, regardless of its timing, aligns with our explanation of non-pecuniary remuneration. In other words, women's preferences for job amenities change due to motherhood, and work in firms providing other advantages and accept wage cuts for these advantages. For example, Lowen and Sicilian (2009) provide evidence that women receive family-friendly fringe benefits. And Felfe (2012) shows that women in Germany adjust along various dimensions when having children, such as hours, work schedule and even level of stress.

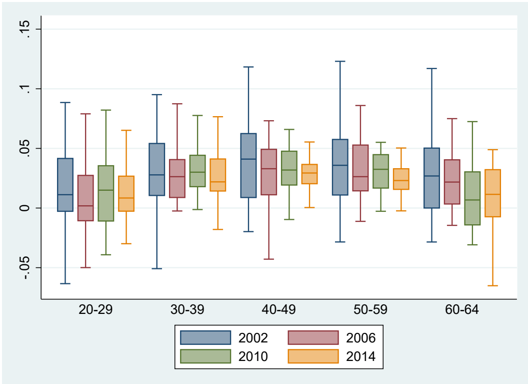
Figure 3.4: Components by Age Group



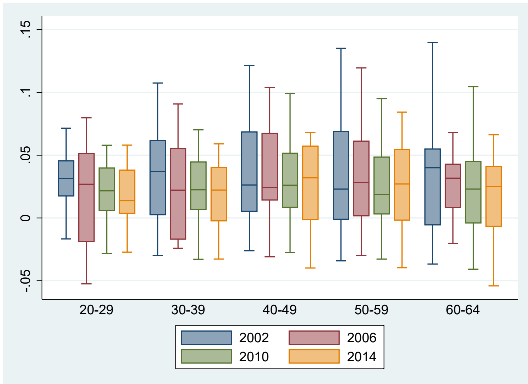
(a) Between-firm component (Male Effects)



(b) Between-firm component (Female Effects)



(c) Within-firm component (Female Distribution)



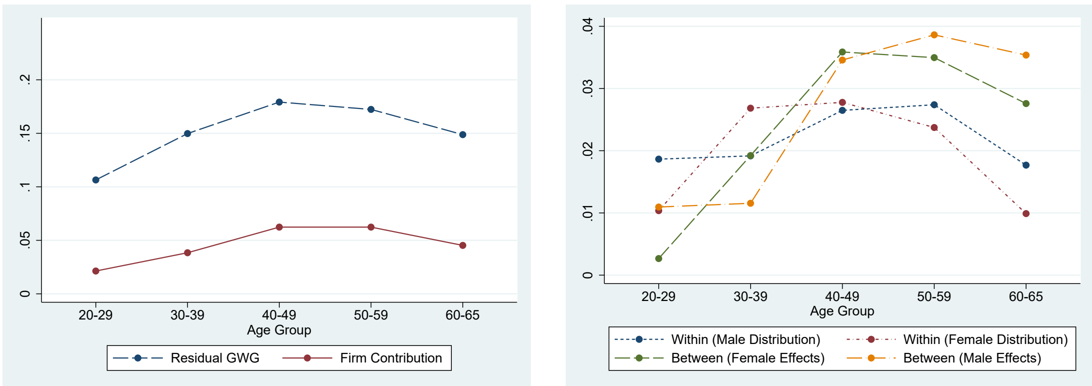
(d) Within-firm component (Male Distribution)

The box plots show the between- and within-firm component in the upper and lower panels, respectively. They differ in terms of whether we use male or female effects or distributions for the former and the latter. The results are based on equations (3.3) and (3.4), which are computed for each age group in the baseline sample with 1 man and 1 woman separately. The fixed effects were normalized using the definition of low-pay. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

Depending on whether exploiting the male or female distribution, the within-firm component changes its form across the life-cycle slightly. With the female distribution shown in panel (c), it takes on the standard life-cycle form seen before and established in the literature, namely an inverse U-shape. However, the form is not very pronounced when taking into consideration only one survey wave at a time. On the other hand, when using the male distribution, the within-firm component is flat across all age groups in a given survey. In line with the previous finding that the within-firm component is falling between 2002 and 2014, this development can be also seen in both panels (c) and (d). In both panels, a substantial decline is visible for nearly all age groups, especially for younger cohorts. These changes over time tend to imply that discrimination towards women has decreased. Xiao (2020) argues that the gender wage gap in early career stages is due to discrimination, what we can also see in the levels of the within-firm component at the early stages of the career as it exceeds the levels of the between-firm component.

Figure 3.5 elaborates on the development of the gender wage gap, the contribution of firms and its two components across the life cycle using the latest wave of the SES. The left panel shows the gender wage gap and the firms' contribution to it across the life cycle. It highlights the importance of the firms' contribution on a European level. Specifically, the percentage of the wage gap that is explained by the firm-specific pay differentials is also taking on an inverse U-shape. For the lowest age category, the firms contribute close to 32 percent to the overall pay gap. It then rises by around 4.5 and 5.5 percentage points for the subsequent two age groups. It reaches its maximum at 44.6 percent for the age group from 50 to 59, and then declines weakly to 41 percent for the last age group. This pattern reinforces the picture of a "scarring" effect of motherhood, and that firms contribute significantly to this development over the life cycle.

Figure 3.5: Life-cycle analysis of the Gender Wage Gap and its Components



(a) Residual GWG and Firm Contribution

(b) Within- and Between-firm component

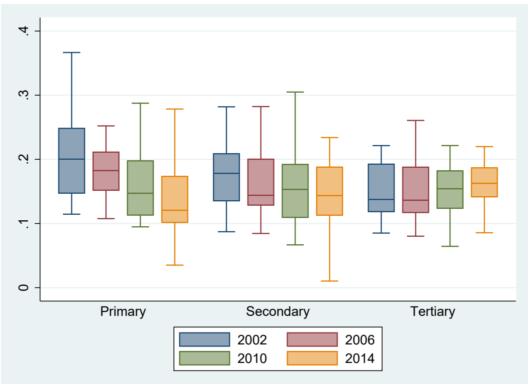
The left panel shows the residual gender wage gap and the firms' contribution to it across the five different age groups in 2014. The values depicted constitute the average across the 20 countries in the 2014 SES data. The firms' contribution is equal to the left-hand side of equation (3.3). The right panel shows the two different components differentiating between the way of computation, as shown in equations (3.3) and (3.4).

The right panel presents the development of the within- and between-firm components of the firm contribution shown in the left panel over the life cycle. Interestingly, the within-firm component tends to be larger than the between-firm component for the youngest two age groups. This speaks to discrimination being the determining factor of the gender wage gap at early stages in the career as pointed out by Xiao (2020). However, for the age category from 40 to 49, the between-firm components overtake the within-firm components in their magnitude. This development indicates that non-pecuniary remuneration pays an important role as argued by Felfe (2012). Family-friendly firms potentially offer these benefits in exchange for wage cuts, and hence women tend to work in low-paying firms due to changing preferences over the life cycle. The importance of the between-firm component does tends to increase for the subsequent two age categories, while the within-firm component starts to fall for the same age groups. This indicates that non-pecuniary remuneration and human capital depreciation are closely interrelated, especially as Angelov et al. (2016) point out that the long-term depreciation rates are much higher than the short-term rates. Therefore, breaks or prolonged part-time work of mothers also implies worse long-term decline in wages and sorting into low-paying firms.

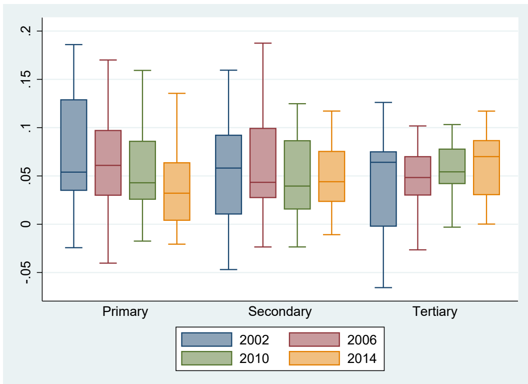
3.4.3.3 Education

We now explore how the gender wage gap, the firms' contribution and the individual components differ across educational levels. This distinction across education category relates to the discussion of sticky floors versus sticky floors, which was first investigated on a European level by Arulampalam et al. (2007) and later by Christofides et al. (2013). Strictly speaking, our analysis by education groups is not perfectly equivalent to the discussion because these studies examine the whole income distribution, but De la Rica et al. (2008) also relate larger gender wage gaps at higher levels educational attainment to glass ceilings for Spain. Our analysis relates insofar to the discussion as higher education typically implies higher incomes. As the SES provides information on education at three different levels, i.e. primary, secondary and tertiary, we will consider primary education the lower part of the income distribution, and tertiary education to the upper part of the distribution. Hence, when relating to the discussion of sticky floors versus glass ceilings, we relate our findings for workers with primary education to the former, and for workers with tertiary education to the latter.

Figure 3.6: Evolution of Firm's Contribution to the Gender Wage Gap by Education



(a) Residual Gender Wage Gap

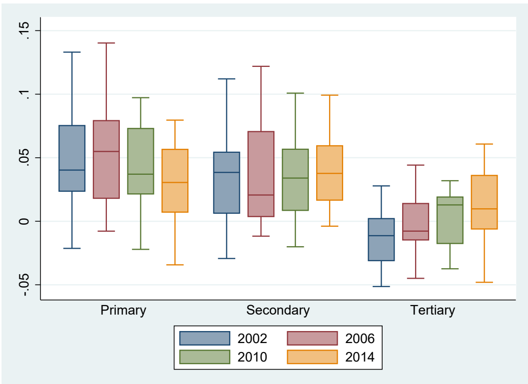


(b) Total Contribution of Firm Components

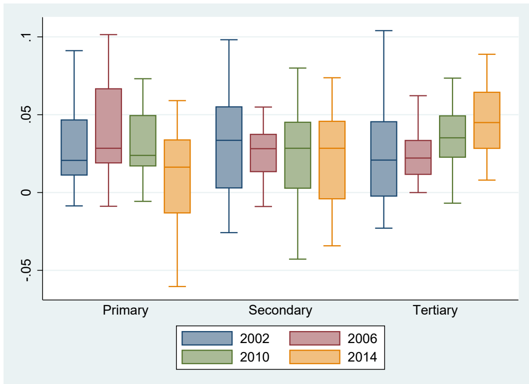
This figure shows the residual wage gap and the firms' contribution to the gender pay gap for three different education groups and across all waves of the SES. The results are based on the analysis explained in Section 3.3 for each education group. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

Figure 3.6 shows the residual wage gap and the firms' contribution to this gap by educational level across all four waves of the SES. It is immediately visible that the unobserved gender wage gap fell most for workers with primary education, slightly for workers with secondary education and nearly no decrease over time for workers with tertiary education. Interestingly, the firms' contribution to the gender pay gap reflects the declines, for the first two educational groups. On the other hand, the contribution of firms to the gender wage gap is increasing over time even though the overall unexplained wage gap between men and women stays constant. Relating these findings to the discussion of sticky floors versus glass ceilings, the glass ceiling seems to become stronger between 2002 and 2014, while the importance of sticky floors seems to decrease over time. Examining both panels in the figure in terms of levels, we see that in 2002 both the residual pay gap and the firms' contribution are (on average) the lowest for secondary education, and slightly higher for both primary and tertiary education. Due to the aforementioned changes over time, this order has changed by 2014: the pay gap now increases with educational level.

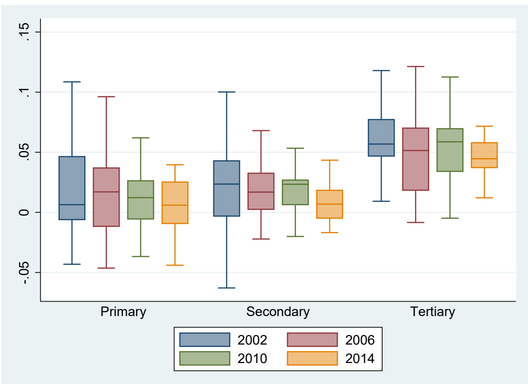
Figure 3.7: Components by Education Group



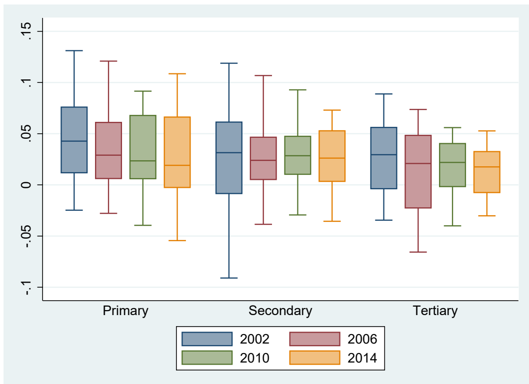
(a) Between-firm component (Male Effects)



(b) Between-firm component (Female Effects)



(c) Within-firm component (Female Distribution)



(d) Within-firm component (Male Distribution)

The box plots show the between- and within-firm component in the upper and lower panels, respectively. They differ in terms of whether we use male or female effects or distributions for the former and the latter. The results are based on equations (3.3) and (3.4), which are computed for each education group in the baseline sample with 1 man and 1 woman separately. The fixed effects were normalized using the definition of low-pay. Each box represents the interquartile range of the respective measure in a given year, and the whiskers indicate the minimum and the maximum, excluding outliers.

We now explore how the within- and between-firm component differ by education category using an analogous structure as before. Figure 3.7 depicts both components with either male or female effects or distribution, with the between-component in the upper panels (a) and (b), and the corresponding within-firm component below. As argued above for the full sample, the between-firm component is not changing much over time. There is a modest decline for workers with primary education, but this effect is completely offset within the group of employees with tertiary education. Regardless of whether we compute the between-firm component with male or female effects, there is a substantial increase within the group of workers with tertiary education.
Given the previous findings about the firms' contribution to the gender pay gap and the between-firm component, the decline of the within-firm components over time across all education groups comes without surprise. The decrease for employees with primary education is somewhat stronger than for those with secondary or tertiary education. One striking difference between panels (c) and (d) is the level of the within-firm component across the different education groups. In particular, the level of this component is smaller for primary and secondary education when using the female distribution compared to the male distribution, and vice versa for tertiary education. This indicates that men with tertiary education are more concentrated in firms with low gender wage gaps, whereas men with primary and secondary education are working primarily in firms with a higher gender premia differential. Thus, the finding for the full sample that men are concentrated in firms with pay gaps is mainly driven by men with primary and secondary education.

3.4.4 Within-firm Gender Wage Gap and Firm Characteristics

The decomposition into a within-firm and between-firm component using firm premia also allows us to compute the firm-specific gender wage gap due to these premia. In the analysis, we will use normalized wage premia based on the definition of low-pay as explained above. We relate these within-firm gaps between men and women to factors commonly referred to in the literature and in Coudin et al. (2018, Table 8). In particular, our specification is closest to Column (2) in their specification, as we include industry-fixed effects and the level of collective bargaining in our regressions. As we are investigating 21 countries, we also include country-fixed effects in all regressions. In the specification including all years, we all employ year-fixed effects. This means that the conditional correlations we obtain between firm observables and the within-firm gender wage relies on variation within sector, within countries and within years. As explained above, we do not have information of firms on value added per worker, so we cannot include information like this in our estimations.
We relate workforce composition variables, the level of collective bargaining, firm size and the type of control with the within-firm gender wage gap. Table 3.3 shows the condi-

tional correlations between the within-firm wage gaps and these observables, in Column (1) for all years, and from Columns (2) to (5) for each survey wave individually. The first category relates to pay agreements, i.e. the level of collective agreement under which more than 50% of the employees in the firm are working. A large literature associates a higher level of collective agreement with lower wage inequality because it compresses the wage distribution, e.g. DiNardo et al. (1996). Heinze and Wolf (2010) support this notion for Germany by showing that firms with collective bargaining agreements reduces the gender wage gap. Also for Germany, Antonczyk et al. (2010) highlight the differences of collective bargaining regimes across the income distribution. On the other hand, Felgueroso et al. (2008) argue that the gender wage gap rises along the wage distribution if the level of bargaining is centralized. The authors explain this with the difference in actual versus negotiated wages, where the former differs more from the latter towards the upper part of the wage distribution due to the rising importance of bonus payments.

Our results indicate that less centralized bargaining is associated with a decline in the gender wage gap. The coefficients are relative to the benchmark category "national coverage". Given the results by Felgueroso et al. (2008), one crucial point is that we account for bonus payments in the computation of log hourly wages, and hence the gender wage gap. If they are more important in more centralized bargaining regimes, this can influence our results and lead to a downward bias in the conditional correlations. Examining the coefficients over time, we see their magnitude falling with the exception of region-industry agreements, and sometimes losing significance altogether. Therefore, our results indicate that national wage bargaining acts conversely to international competition as argued by Black and Brainerd (2004). The authors find that product market competition reduces the gender wage gap, while it raises wage inequality.

The next two firm characteristics refer to firm size and type of control, i.e. public or private. Considering the results including all four waves of the SES, larger firms are associated with larger within-firm gender wage gaps relative to firms with less than 50 employees. Oi and Idson (1999, Table 6) provides indirect evidence of this phenomenon. Comparing hourly wages for men and women across different sectors in the United States, the gender wage gap is larger across most industries in firms with more than 1000 workers compared to firms with less than 25 employees and the total wage gap within the sector. Comparing the evolution of our coefficients for firm size across the four survey years, they tend to fall in absolute magnitude and lose significance the latest in 2014. The coefficient for private control is always positive and significant at all conventional levels. Miller (2009) shows for the United States that the gender wage gap is smaller in the public sector at all points in the distribution, though the gap is widening stronger at the top.[11] Frederickson (2010) argues that the values of representation and fairness in the public sector directly imply lower gender wage gaps.

[11] For a review also on differences between private and public sector, see Bishu and Alkadry (2017).

Table 3.3: Within-Firm Gender Wage Gap in Firm Premia

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	-1.053***	-1.061	-1.491**	-0.427**	-1.050***
	(0.000)	(0.105)	(0.020)	(0.045)	(0.000)
Region-Industry Agreement	-1.284***	0.319	-1.703**	-0.355	-1.979***
	(0.000)	(0.662)	(0.016)	(0.399)	(0.000)
Enterprise agreement	-1.401***	-2.045***	-1.614**	0.008	-2.153***
	(0.000)	(0.003)	(0.018)	(0.976)	(0.000)
Local Unit Agreement	-0.952	-2.113	-1.766**	1.298	-5.245*
	(0.297)	(0.250)	(0.039)	(0.399)	(0.083)
Other agreement	-4.393***	-4.612***	-5.181***	0.382	-1.990
	(0.000)	(0.000)	(0.000)	(0.765)	(0.413)
No agreement	-1.549***	-2.186***	-4.074***	-0.078	-1.865
	(0.000)	(0.000)	(0.000)	(0.922)	(0.196)
Firm Size					
50-249 Employees	1.070***	1.419***	1.217***	1.322***	0.725
	(0.000)	(0.000)	(0.000)	(0.000)	(0.396)
250+ Employees	1.081***	0.106	-0.376	0.239	1.078
	(0.000)	(0.708)	(0.138)	(0.247)	(0.206)
Control					
Private	2.605***	3.099***	0.891	1.658***	2.740***
	(0.000)	(0.000)	(0.120)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	-0.006**	-0.025***	-0.017***	-0.019***	-0.006
	(0.024)	(0.000)	(0.001)	(0.001)	(0.190)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.311***	0.226***	0.284***	0.352***	0.322***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.055***	0.047***	0.040***	0.065***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clerks (%)	0.031***	-0.018***	-0.014**	0.087***	0.025***
	(0.000)	(0.001)	(0.018)	(0.000)	(0.000)
Female among Executives (%)	-0.166***	-0.140***	-0.199***	-0.109***	-0.184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among White Collars (%)	0.034***	0.041***	-0.004	-0.015***	0.046***
	(0.000)	(0.000)	(0.190)	(0.000)	(0.000)
Female among Clerks (%)	0.026***	0.068***	0.089***	0.034***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Blue Collars (%)	0.056***	0.032***	0.038***	0.065***	0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%)	-0.011***	-0.092***	-0.083***	0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Low Pay Earners (%F-%M)	0.353***	0.272***	0.366***	0.352***	0.354***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	413035	70918	118750	95955	127412
R^2	0.21	0.16	0.23	0.24	0.22

Notes: The dependent variable is the difference in firm premia (male minus female) based on estimated firm-fixed effects for each gender. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Finally, we investigate how the within-firm gender wage gaps is related to workforce composition. The signs of the coefficients for the share of temporary and part-time workers changes throughout the specifications. However the share of executives is strongly associated with a rise in the within-firm gender wage gap. This can be due to the glass ceiling mentioned above due to a lack of access of women to management positions or even supervisory positions within firms as argued by Bishu and Alkadry (2017). A one percentage point increase in the share of executives is related to a .41 percentage point increase in the within-firm wage gap in the specification with all years, i.e. Column (1). However, a larger share of females among executives reduces the gender wage gap, which can have two explanations. First, the women in management positions also get a higher (hourly) wage and hence directly contribute to the decrease in firm wage gaps. Second, as Cardoso and Winter-Ebmer (2010) argue, female non-management workers also profit from female executives in terms of promotion and mentoring, and subsequently in terms of wages.

The share of workers earning below the definition of low-pay, which is equal to two-thirds of the median wage, is associated with a decrease in the gender wage gap. However, more women earn wages below this threshold. Therefore, as the coefficient for the difference of female share relative to the male share earning below this threshold, this has a strong negative impact on the gender wage gap. In fact, the magnitude of the coefficient is nearly identical with the share of executives in the specification including all waves of the SES. Other occupational shares, such as white collars and clerks, are related to a rise in the within-firm gender wage gap, similar to the analysis in Coudin et al. (2018).

3.4.5 Between-firm analysis

After examining conditional correlations of the within-firm gender wage gap with and firm observables, we now investigate the between-firm component. By definition, this measure is not available on the firm-level. Due to the lack of information of job amenities on a more detailed level, such as occupation or sector of economic activity, our sample with country-year differences lacks variation for a more in-depth analysis. As is standard with cross-country panel regressions, independent of the number of explanatory variables, the potential for omitted variable bias is large. Therefore, we do not focus on the estimates per se, but rather put the emphasis on coefficients' signs and their relative magnitude across the different subgroups subject to scrutiny.

We compute unconditional correlations of the between-firm component with family policy indicators by the OECD. We focus on family policy for two reasons. First, our findings of the between-firm component indicates that it is rising across the life-cycle and related to motherhood. Second, the recent literature links an increase in the gender wage gap to motherhood. Olivetti and Petrongolo (2017) argue that family policy in developed economies has the idea to guarantee equity between men and women by allowing women to combine careers and motherhood. While we focus on the hourly wage gap as this has been subject to the analysis above, family policy can also influence other labor market outcomes of women, such as employment. Further, family policy is complex and can vary in many dimensions. Therefore, we pick eight different indicators to get a complete picture.

Our analysis is similar to Christofides et al. (2013, Fig. 3) in terms of its goal, i.e. we want to examine correlations of family policy on a component of the gender wage gap. However, there are a few important differences. First, the authors focus on the overall unexplained gender wage gap, we concentrate on the between-firm component. Second, instead of concentrating on an overall family-and work reconciliation index, we focus on single measures. Third, instead of comparing differences across the wage distribution, we rather compare age subgroups as explained previously. Finally, we possess more variation as we investigate four different waves, while the authors exploit cross-country variation.
Table 3.4 shows the correlations between various family policies ranging from expenditure, length of parental leave and child enrolment and the between-firm component. The upper panel uses the between-firm component computed with male effects, while the component in the lower panel is computed with female effects. Columns (1) to (4) focus on total public expenditure (in percent of GDP) on families and its subcomponents including cash, services and taxes. All signs of the components are negative except for the expenditure related to tax when computing the between-firm component using female effects. However, only the expenditure on services is statistically significant in both the upper and lower panel for the full sample. In particular, what holds for both specifications is that primarily women above the age of 30, i.e. shortly after the average European woman gets her first child, the coefficient turns significant and it rises in absolute magnitude. The significance peters off with rising age, but it is significant for both age groups 30 to 39 and 40 to 49.
The next area of family policy relates to parental leave regimes in columns (5) and (6). As Olivetti and Petrongolo (2017) argue, this issue within family policies is potentially the most complex as there are many dimensions, such as length, job protection, income support and eligibility to both partners. Therefore, it has been subject to many empirical studies, e.g. Ruhm (1998) and Nielsen et al. (2004). We focus on the length of parental leave for both mothers and fathers as they are found to have a stronger impact on earnings, whereas other factors rather relate to employment status. Maternity and paternity leave are both measured in weeks and vary strongly across countries in the sample, i.e. the former ranges between 16 and 166 weeks, and the latter between zero and 28 weeks. Maternity leave can lead to either changes in preferences for non-pecuniary remuneration as argued by Felfe (2012) or can be related to long-term depreciation in human capital. Both explanations lead to an increase of the gender pay gap across the cycle, though the

Table 3.4: Between-Firm Gender Wage Gap in Firm Premia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male Effects	Expenditure (Total)	Expenditure (Cash)	Expenditure (Services)	Expenditure (Tax)	Length Maternity Leave	Length Paternity Leave	Childcare Enrollment 0-2 (%)	Childcare Enrollment 3-5 (%)
Total	-1.747***	-1.990***	-2.716***	-2.100	0.005	-0.066	-0.077***	-0.111***
	(0.000)	(0.001)	(0.000)	(0.117)	(0.405)	(0.140)	(0.000)	(0.002)
20-29	-2.071***	-2.933***	-1.621**	-4.656***	-0.003	0.004	-0.009	-0.040
	(0.000)	(0.000)	(0.044)	(0.002)	(0.661)	(0.939)	(0.741)	(0.388)
30-39	-1.701***	-1.504**	-2.983***	-1.771	0.020***	-0.073	-0.108***	-0.163***
	(0.001)	(0.036)	(0.000)	(0.281)	(0.006)	(0.169)	(0.000)	(0.000)
40-49	-1.774***	-1.613**	-3.386***	-1.146	0.006	-0.096*	-0.111***	-0.146***
	(0.000)	(0.015)	(0.000)	(0.462)	(0.440)	(0.064)	(0.000)	(0.000)
50-59	-1.174**	-1.545**	-2.395***	-2.101	-0.007	-0.122**	-0.057**	-0.071
	(0.026)	(0.034)	(0.003)	(0.193)	(0.383)	(0.028)	(0.040)	(0.120)
60-64	-2.896***	-3.866***	-1.548	-4.754*	-0.028**	0.005	-0.005	0.042
	(0.000)	(0.000)	(0.217)	(0.052)	(0.019)	(0.958)	(0.911)	(0.564)
Female Effects								
Total	-0.887**	-0.844	-1.975***	1.471	0.014**	-0.065	-0.067***	-0.088**
	(0.032)	(0.136)	(0.001)	(0.246)	(0.015)	(0.128)	(0.002)	(0.019)
20-29	-0.317	-0.078	-0.718	-1.669	0.022***	-0.019	-0.037	-0.113***
	(0.510)	(0.915)	(0.382)	(0.246)	(0.001)	(0.723)	(0.176)	(0.009)
30-39	-0.771	0.163	-2.476***	0.789	0.033***	-0.107*	-0.102***	-0.156***
	(0.191)	(0.831)	(0.003)	(0.659)	(0.000)	(0.062)	(0.000)	(0.001)
40-49	-1.130**	-1.141	-2.286***	3.094**	0.005	-0.074	-0.079***	-0.061
	(0.026)	(0.128)	(0.006)	(0.044)	(0.549)	(0.172)	(0.004)	(0.215)
50-59	-1.149**	-2.244***	-1.693*	2.104	-0.014*	-0.064	-0.025	0.009
	(0.023)	(0.003)	(0.053)	(0.174)	(0.072)	(0.272)	(0.362)	(0.850)
60-64	-1.283**	-2.676***	0.137	0.497	-0.015	0.074	0.026	0.019
	(0.033)	(0.003)	(0.896)	(0.789)	(0.136)	(0.293)	(0.459)	(0.718)
Observations	47	64	64	47	55	55	52	46

Notes: The dependent variable is the between-firm component, the upper panel makes use of the male effects while the lower panel makes use of female effects. The table shows correlations between the two different between-firm components and various OECD indicators regarding public policies for families and children. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

former indicates a sudden rise after motherhood, whereas the latter implies a slowly rising gender wage gap across the life cycle.

In line with Ruhm (1998) and OECD (2012), a longer maternity leave is associated with higher gender pay gaps, though we find that the effect is most crucial for the group of 30-39 in both panels, whereas for the full sample and the age group 20-29 it has no impact. For higher age groups, this effect is diminishing and even changes signs.[12] On the other hand, paternity leave is hardly ever statistically significant on conventional levels, which can be due to the lower level of variation in paternity leave as mentioned above. However, the signs also indicate room for importance of paternity (besides maternity) leave. While the signs are positive for the full sample and the age group from 20 to 29, the sign turns negative and the coefficient is even statistically significant at 10% in the lower panel for the age group of 30 to 39. The sign does not change again until the age group of 60 to 64, hence paternity leave seems to be a potential policy for mitigating the "scarring" effect of motherhood. Patnaik (2019) examines the impact of paternity leave with very generous compensation on various labor market outcomes of women. Especially employment status and hours worked (conditional on employment) of mothers improve. She also finds long-term effects of paternity leave, for which we get suggestive evidence.

Finally, we consider child enrolment (in percent) in pre-primary education or primary school for children both between zero and two, and three to five. Both indicators exhibit a strong positive correlation with expenditure in services, namely .70 and .51, respectively. Hence, the results are not very surprising, i.e. a higher enrolment in both age groups is associated with a lower between-firm component, and subsequently a lower gender pay gap. This holds particularly for the age group 30 to 39 in both panels. This effect seems to have an impact on the subsequent age group (40 to 49), though the estimates are smaller relative to the group 30 to 39, and the coefficients are estimated with more noise.

3.4.6 Robustness Analyses

To test for the validity of the baseline results shown above, this paper applies two sensitivity analyses. The first accounts for possible bias by not fully identifying the firm-fixed effects in the baseline sample due to the requirement to observe only one man and one woman per firm. This minimum requirement for the decomposition can lead to a bias in firm-fixed effects, and hence pay premia, if they contain unobserved employee components which systemically differ between men and women. This bias can be stronger for small firms, where we do not observe many employees, and if one gender works primarily in small firms this can influence the differential pay premia after decomposition. The tables for the first sensitivity analysis are in Appendix 3.3.

[12] One issue with older age groups and family policy indicators is that they are likely to be less subject to the contemporaneous family policies, and were rather affected through the policy regime in place around their family formation.

For our first robustness analysis we require to observe at least five male and female employees per firm. This tends to eliminate small firms, but this stronger requirement ensures that unobserved worker characteristics influence the firm-fixed effects except if these unobserved characteristics of the randomly employees do not cancel out in the mean. We repeat the whole analysis, starting with the estimation of the residual wage gap based on worker observables, the estimation of firm fixed effect and the test whether female fixed effects are smaller than male fixed effects for firms paying below the country-year specific threshold of low-pay according to the definition of the OECD. The results for the Mincer equation with this sample are shown in Table D1 and the results are qualitatively comparable to the baseline estimations. We also check the condition to obtain lower-bound estimates of the within-firm component of $\hat{\psi}^F < \hat{\psi}^M$ from equation (3.2) in Table D2. The first result is that the (non-normalized) estimated gender-specific firm premia tend to be larger in this sample, which does not come as a surprise given the stronger focus on larger firms due to the data requirement. Besides the previously mentioned two cases where the condition does not hold, two other cases emerge for this sample, namely Hungary in 2006 and Norway in 2002. So we still obtain lower-bound estimates of the within-firm component for the majority of observations.

Next, we decompose the new firm premia into their within- and between-firm components based on equations (3.3) and (3.4). Tables D3 to D6 show the residual gender wage gap, the gender-specific firm premia (after normalization), the resulting contribution of firms to the gender wage gap, and both the between- and within-firm components depending on computation. In none of the indicators there is a one-sided bias: some values are larger than in the baseline sample, whereas others are smaller. Importantly, there is no change in the relative importance of the components and their evolution across the four waves. In other words, this requirement does not change any of the findings for the full sample in the baseline estimations. This also holds largely with respect to the age and education subgroups with one exception.

Compared with the baseline results, we find one small exception, namely for educational subgroups, and it refers to the between-firm component and their different measurement. In the baseline results, we find different levels of the between-firm component for the group of workers with tertiary education depending on whether we use male or female effects for its computation. In the robustness analysis, the levels are very similar regardless of the way of computation, just like for workers with primary and secondary education in the baseline analysis. in Figure 3.7. Hence, this sample (with larger firms) seems to clarify the issue found above and speaks to the concentration of men relative to the gender gap in firm premia.

The second robustness check refers to the type of normalization, and its results are shown in Appendix 3.5. While Card et al. (2016) and Coudin et al. (2018) possess information on value added per worker on the firm level, and thus can infer match surpluses between employers and employees, we do not possess this information. Therefore in the baseline, we use actual wages containing surpluses and implicitly assume that wages from low-wage firms contain the smallest premiums. In the sensitivity analysis, we normalize by firms in the hotel and restaurant industry, which is considered a low-surplus sector, for the sample with at least one male and female worker per firm. This is motivated by Card et al. (2016) and references therein, e.g. Krueger and Summers (1988). As the crucial change to the analysis only occurs after the estimation of the firm-fixed effects, and hence after the estimation of residual wages, we start by comparing (non-normalized) gender-specific average fixed effects. Table E1 presents the estimated firm premia for men and women by country and year for the hotel and restaurant industry. Keeping in mind that in order to obtain lower-bound estimates for the within-firm component, the firm premia of women need to be smaller than four men. The results show that only in two cases this condition is not met, specifically in Latvia in 2002 and 2010.

Tables E2 to E5 present the decomposition results analogous to the baseline analysis and the first robustness analysis. The results for this normalization also do not indicate any specific bias on a country-year basis. This holds for all variables of interest in these tables, i.e. the gap in residual wages, the firms' contribution to this gap, as well as the within- and between-firm component. As before, both components are somewhat equally important and the within-firm component is falling over time, while the between-firm component stays constant. If at all, the within-firm component is declining stronger across the four waves of the SES compared to the baseline estimation. The tables support this for the full sample, but no part of the analysis of the subsamples by age and education is affected by the different normalization. The change in the between-component for tertiary education of the previous robustness analysis is not confirmed, hence this change is likely due to a slightly different sample composition with less smaller firms.

Given that none of the previous messages changes substantially, it is not surprising that the subsequent analysis of firm observables with average premia or the individual components changes qualitatively. The tables are shown in appendices 3.4 and 3.5 for the subsample requiring 5 workers of each gender and for the alternative specialization using firms from the hotel and restaurant sector, respectively. Some estimates, which were close to zero in the baseline analysis in the analysis of average firm premia may change sign, but stay close to zero, e.g. the share of clerks. Overall, no covariates of higher interest change their sign in the analysis of the within- and between-firm components. Finally, we do not need to analyze the between-firm component for the alternative normalization with the hotel and restaurant industry because, as argued above, this component is unaffected by the type of normalization.

3.5 Conclusion

We investigate the contribution of gender-specific firm premia to the gender wage gap for a large majority of European countries. We make use of the Structure of Earnings Survey provided by Eurostat, a harmonized matched employer-employee data set. We exploit the methodology of Card et al. (2016) to estimate the firms' contribution to the gender pay gap and decompose this contribution into a within- and between-firm component. We discuss three underlying explanations for why the gender wage gap changes across the life cycle, namely non-pecuniary remuneration, loss of human capital and discrimination. Importantly, we associate each component to either one or both of the explanations for the gender wage gap.

We find that firm-specific pay differentials between men and women contribute around 35 percent of the overall residual gender wage gap, with large heterogeneity across countries. The decomposition shows that in total, the within- and between-firm component contribute equally to the pay gap. Between 2002 and 2014, the former has declined, whereas the latter has stayed nearly unchanged over the time period. This finding shows that the overall decline in the gender pay gap is entirely driven by the within-firm component. Investigating the components across educational groups, we see that the decline in the within-firm component across the four survey waves is shared across all groups. However, in the group of workers with tertiary education, a rise in the between-firm component counteracts this decline of the within-component. We relate the lack of falling wage gaps within this group of workers to the glass ceiling as documented by Christofides et al. (2013) for Europe.

An established finding in the literature is that the gender wage gap is rising over the life cycle. We investigate how the two different components change over the life cycle, and in line with Coudin et al. (2018) for France, we find that the between-firm component is rising stronger across the life cycle. For the age 20 to 29, the average within-firm component is larger than the between-firm component. By the age group of 40 to 49, the between-firm components using either computation exceed the within-firm components, and this order does not change for the rest of the life cycle. Hence, the between-firm component plays a crucial role for the rise in the gender wage gap over the working life. This is likely due to explanations relating to motherhood, i.e. changing preferences with respect to non-pecuniary remuneration and human capital depreciation. The findings by Delfino (2019) suggest that men tend to sort negatively into female-dominated occupations due to a lack of expected returns to ability. To reduce the between-firm component, policies to break gender barriers should go in both directions: Support women to take on high-paying occupations, and to encourage men to go into female-dominated occupations.

In the last step of our analysis, we relate the within- and the between-firm component to institutional settings, the former to collective bargaining and the latter to family policy.

Even though a higher level of centralization in the wage bargaining process is typically associated with less wage inequality, we find that it does not reduce the within-firm gender wage gap. Instead, lower levels of centralization are associated with lower levels of the gender wage gap. This indicates that our results for collective bargaining are converse to the findings for product market competition by Black and Brainerd (2004), who show that competition raises wage inequality and reduces the gender wage gap. Finally, we link various indicators of family policy to the between-firm component. Importantly, we distinguish between age groups as the between-firm component increases over the life cycle. We find that higher social spending on families and children enrolment reduce the gender wage gap in particular in the age group of 30 to 39, and then tend to peter off over the life cycle. For maternity leave, we confirm previous findings that longer periods increase the gender wage gap, and the effect also starts for the same age group. While the correlation between paternity leave and the gender wage gap are not statistically significant, our results suggest a potential for reducing gender wage gaps. Miyajima and Yamaguchi (2017) suggest that men would like to take paternity leave, but do not dare doing so. Policies should be designed in a way to encourage men to take paternity leave to overcome gender role norms in order to achieve greater wage parity between men and women.

3.1 Data Availability and Comparisons of Descriptive Statistics

Table A1: Data Availability

Country	Code	2002	2006	2010	2014	Reason of Exclusion
Belgium	BE	Y	Y	Y	Y	
Bulgaria	BG	Y	Y	Y	Y	
Cyprus	CY	Y	Y	Y	Y	
Czech Republic	CZ	Y	Y	Y	Y	
Germany	DE	X	Y	Y	Y	
Estonia	EE	Y	Y	Y	Y	
Greece	EL	Y	Y	Y	Y	
Spain	ES	Y	Y	Y	Y	
Finland	FI	(Y)	(Y)	(Y)	(Y)	No firm identifier
France	FR	Y	Y	Y	Y	
Croatia	HR	X	X	X	Y	Lack of consecutive years
Hungary	HU	Y	Y	Y	Y	
Italy	IT	Y	Y	Y	Y	
Lithuania	LT	Y	Y	Y	Y	
Luxembourg	LU	(Y)	(Y)	(Y)	(Y)	No firm identifier
Latvia	LV	Y	Y	Y	Y	
Malta	MT	(Y)	(Y)	(Y)	Y	Pre-2014 data only in Safe Center
Netherlands	NL	Y	Y	Y	Y	
Norway	NO	Y	Y	Y	Y	
Poland	PL	Y	Y	Y	Y	
Portugal	PT	Y	Y	Y	Y	
Romania	RO	Y	Y	Y	Y	
Sweden	SE	(Y)	Y	Y	Y	No information on tenure in 2002
Slovenia	SI	X	X	X	(Y)	Lack of consecutive years
Slovakia	SK	Y	Y	Y	Y	
United Kingdom	UK	(Y)	Y	Y	Y	Only one worker per firm in 2002

The table does not show Austria (AT), Denmark (DK) or Ireland (IE) because the SES was not conducted in these countries in any given year. The SES for Sweden in 2002 does not possess information on tenure, so it is not included either as it does not allow for the estimation of the wage residual. “X” indicates that the data is not available, and “(Y)” indicates that the data is available, but lacks information for estimating the gender wage gap. Finally, “Y” indicates that we use the sample in our analysis.

Table A2: Descriptive Statistics for various samples of Employers in SES (2002)

	(1) **Original Data**	(2) **Cleaned Data (1)**	(3) **Cleaned Data (5)**
10-49 Employees (%)	0.460	0.427	0.252
50-249 Employees (%)	0.262	0.275	0.334
$>$ 249 Employees (%)	0.278	0.298	0.414
Public Control	0.089	0.099	0.167
Private Control	0.909	0.899	0.830
MQEWS	0.037	0.035	0.045
Manufacturing	0.331	0.351	0.392
Construction	0.082	0.064	0.043
Wholesale and Retail	0.236	0.221	0.179
Hotels and Restaurants	0.045	0.047	0.040
Transport, Storage, Communication	0.084	0.079	0.092
Financial Intermediation	0.057	0.065	0.071
Real Estate and Business Activities	0.129	0.137	0.138
National Agreement (%)	0.203	0.207	0.083
Industry Agreement (%)	0.120	0.120	0.092
Region-Industry Agreement (%)	0.076	0.063	0.022
Enterprise Agreement (%)	0.128	0.149	0.238
Local Unit Agreement (%)	0.003	0.003	0.002
Agreement (Other) (%)	0.053	0.026	0.010
No Agreement (%)	0.190	0.206	0.233
Average Wage below Low Pay (%)	0.131	0.140	0.175
Number of Employers	133473	91934	27518

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various firm characteristics, including level of collective pay agreement , sector of activity, public control and the share of firms paying below . It also includes the total number of firms observed in each sample.

Table A3: Descriptive Statistics for various samples of Employers in SES (2006)

	(1) **Original Data**	(2) **Cleaned Data (1)**	(3) **Cleaned Data (5)**
10-49 Employees (%)	0.421	0.347	0.172
50-249 Employees (%)	0.211	0.226	0.251
$>$ 249 Employees (%)	0.367	0.426	0.577
Public Control	0.055	0.065	0.101
Private Control	0.860	0.840	0.779
MQEWS	0.032	0.035	0.039
Manufacturing	0.292	0.337	0.397
Construction	0.082	0.063	0.035
Wholesale and Retail	0.246	0.219	0.174
Hotels and Restaurants	0.045	0.046	0.041
Transport, Storage, Communication	0.082	0.075	0.067
Financial Intermediation	0.068	0.068	0.071
Real Estate and Business Activities	0.152	0.156	0.175
National Agreement (%)	0.093	0.127	0.184
Industry Agreement (%)	0.225	0.232	0.209
Region-Industry Agreement (%)	0.060	0.057	0.028
Enterprise Agreement (%)	0.156	0.205	0.292
Local Unit Agreement (%)	0.011	0.008	0.002
Agreement (Other) (%)	0.120	0.032	0.010
No Agreement (%)	0.264	0.270	0.216
Average Wage below Low Pay (%)	0.109	0.119	0.111
Number of Employers	234199	134715	44887

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various firm characteristics, including level of collective pay agreement , sector of activity, public control and the share of firms paying below . It also includes the total number of firms observed in each sample.

Table A4: Descriptive Statistics for various samples of Employers in SES (2010)

	(1) **Original Data**	(2) **Cleaned Data (1)**	(3) **Cleaned Data (5)**
10-49 Employees (%)	0.430	0.387	0.242
50-249 Employees (%)	0.230	0.273	0.349
$>$ 249 Employees (%)	0.321	0.317	0.395
Public Control	0.057	0.065	0.089
Private Control	0.724	0.658	0.664
MQEWS	0.038	0.042	0.040
Manufacturing	0.218	0.269	0.328
Construction	0.078	0.059	0.032
Wholesale and Retail	0.233	0.186	0.142
Hotels and Restaurants	0.049	0.044	0.041
Transport, Storage, Communication	0.129	0.132	0.141
Financial Intermediation	0.069	0.074	0.079
Real Estate and Business Activities	0.187	0.194	0.198
National Agreement (%)	0.191	0.232	0.246
Industry Agreement (%)	0.163	0.186	0.180
Region-Industry Agreement (%)	0.011	0.016	0.020
Enterprise Agreement (%)	0.092	0.123	0.188
Local Unit Agreement (%)	0.015	0.003	0
Agreement (Other) (%)	0.095	0.024	0.007
No Agreement (%)	0.221	0.151	0.144
Average Wage below Low Pay (%)	0.055	0.060	0.054
Number of Employers	280937	138872	47543

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various firm characteristics, including level of collective pay agreement , sector of activity, public control and the share of firms paying below . It also includes the total number of firms observed in each sample.

Table A5: Descriptive Statistics for various samples of Employers in SES (2014)

	(1) **Original Data**	(2) **Cleaned Data (1)**	(3) **Cleaned Data (5)**
10-49 Employees (%)	0.400	0.321	0.198
50-249 Employees (%)	0.291	0.336	0.375
$>$ 249 Employees (%)	0.291	0.321	0.413
Public Control	0.061	0.084	0.126
Private Control	0.908	0.873	0.826
MQEWS	0.042	0.050	0.055
Manufacturing	0.198	0.238	0.310
Construction	0.081	0.058	0.030
Wholesale and Retail	0.236	0.202	0.152
Hotels and Restaurants	0.059	0.056	0.048
Transport, Storage, Communication	0.126	0.128	0.132
Financial Intermediation	0.053	0.064	0.076
Real Estate and Business Activities	0.204	0.205	0.199
National Agreement (%)	0.263	0.246	0.176
Industry Agreement (%)	0.205	0.264	0.231
Region-Industry Agreement (%)	0.040	0.047	0.023
Enterprise Agreement (%)	0.109	0.153	0.253
Local Unit Agreement (%)	0.016	0.005	0.002
Agreement (Other) (%)	0.013	0.014	0.008
No Agreement (%)	0.341	0.251	0.279
Average Wage below Low Pay (%)	0.079	0.088	0.094
Number of Employers	294640	139204	40629

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various firm characteristics, including level of collective pay agreement , sector of activity, public control and the share of firms paying below . It also includes the total number of firms observed in each sample.

Table A6: Descriptive Statistics for various samples of Employers in SES (2002)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Data		**Cleaned Data (1 man & woman)**		**Cleaned Data (5 men & women)**	
	Males	Females	Males	Females	Males	Females
Log Hourly Wage	2.709	2.639	2.807	2.687	2.964	2.812
Primary education (%)	0.364	0.283	0.325	0.272	0.265	0.231
Secondary education (%)	0.463	0.515	0.484	0.523	0.544	0.569
Tertiary education (%)	0.173	0.202	0.191	0.206	0.192	0.199
Age 20-29 (%)	0.209	0.258	0.207	0.250	0.200	0.224
Age 30-39 (%)	0.308	0.308	0.302	0.308	0.285	0.294
Age 40-49 (%)	0.278	0.281	0.283	0.286	0.292	0.313
Age 50-59 (%)	0.187	0.144	0.189	0.148	0.201	0.162
Age 60-65 (%)	0.018	0.008	0.019	0.008	0.022	0.008
Managers (%)	0.064	0.050	0.066	0.048	0.062	0.045
Professionals (%)	0.071	0.070	0.079	0.073	0.085	0.091
Technicians (%)	0.130	0.164	0.138	0.166	0.140	0.170
Clerks (%)	0.103	0.258	0.109	0.265	0.111	0.236
Service workers (%)	0.071	0.128	0.077	0.116	0.069	0.099
Craft (%)	0.268	0.112	0.246	0.110	0.254	0.122
Operators (%)	0.194	0.118	0.195	0.123	0.199	0.138
Elementary (%)	0.100	0.101	0.091	0.099	0.080	0.099
Part Time (%)	0	0	0	0	0	0
Temporary Contract (%)	0.077	0.076	0.059	0.072	0.048	0.061
Number of employees	2042882	1129244	1875816	1090910	1426994	874205

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various employer characteristics, including the log hourly wages and the shares of groups by education, age, occupation, part-time and temporary contracts. It also includes the total number of employees observed in each sample.

Table A7: Descriptive Statistics for various samples of Employers in SES (2006)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Data		**Cleaned Data (1 man & woman)**		**Cleaned Data (5 men & women)**	
	Males	Females	Males	Females	Males	Females
Log Hourly Wage	2.550	2.231	2.514	2.233	2.456	2.124
Primary education (%)	0.274	0.223	0.246	0.219	0.211	0.219
Secondary education (%)	0.511	0.532	0.531	0.537	0.579	0.571
Tertiary education (%)	0.215	0.246	0.223	0.244	0.210	0.210
Age 20-29 (%)	0.192	0.247	0.188	0.238	0.183	0.220
Age 30-39 (%)	0.297	0.305	0.297	0.305	0.293	0.298
Age 40-49 (%)	0.286	0.269	0.288	0.274	0.290	0.285
Age 50-59 (%)	0.194	0.165	0.197	0.169	0.206	0.184
Age 60-65 (%)	0.031	0.015	0.029	0.014	0.029	0.013
Managers (%)	0.082	0.074	0.078	0.070	0.056	0.045
Professionals (%)	0.088	0.081	0.097	0.084	0.110	0.092
Technicians (%)	0.136	0.168	0.149	0.170	0.164	0.174
Clerks (%)	0.090	0.269	0.100	0.273	0.113	0.253
Service workers (%)	0.059	0.139	0.060	0.122	0.054	0.102
Craft (%)	0.254	0.076	0.237	0.079	0.228	0.097
Operators (%)	0.187	0.092	0.181	0.098	0.180	0.119
Elementary (%)	0.102	0.099	0.097	0.102	0.093	0.116
Part Time (%)	0	0	0	0	0	0
Temporary Contract (%)	0.097	0.104	0.088	0.104	0.096	0.121
Number of employees	3313570	1716316	3035814	1649609	2324151	1372367

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various employer characteristics, including the log hourly wages and the shares of groups by education, age, occupation, part-time and temporary contracts. It also includes the total number of employees observed in each sample.

Table A8: Descriptive Statistics for various samples of Employers in SES (2010)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Data		**Cleaned Data (1 man & woman)**		**Cleaned Data (5 men & women)**	
	Males	Females	Males	Females	Males	Females
Log Hourly Wage	3.042	2.843	3.063	2.853	3.128	2.891
Primary education (%)	0.125	0.140	0.123	0.140	0.118	0.145
Secondary education (%)	0.743	0.744	0.741	0.747	0.722	0.740
Tertiary education (%)	0.131	0.116	0.136	0.113	0.160	0.116
Age 20-29 (%)	0.175	0.263	0.174	0.261	0.172	0.257
Age 30-39 (%)	0.235	0.226	0.235	0.225	0.240	0.227
Age 40-49 (%)	0.330	0.283	0.331	0.285	0.334	0.287
Age 50-59 (%)	0.223	0.200	0.222	0.202	0.221	0.204
Age 60-65 (%)	0.037	0.027	0.037	0.027	0.034	0.025
Managers (%)	0.038	0.025	0.039	0.024	0.042	0.022
Professionals (%)	0.085	0.070	0.089	0.069	0.105	0.071
Technicians (%)	0.199	0.213	0.207	0.214	0.227	0.215
Clerks (%)	0.092	0.334	0.096	0.339	0.110	0.341
Service workers (%)	0.050	0.143	0.051	0.134	0.050	0.116
Craft (%)	0.285	0.052	0.274	0.053	0.227	0.053
Operators (%)	0.151	0.071	0.146	0.073	0.136	0.083
Elementary (%)	0.099	0.092	0.099	0.094	0.101	0.099
Part Time (%)	0	0	0	0	0	0
Temporary Contract (%)	0.055	0.078	0.057	0.078	0.062	0.083
Number of employees	3378010	1776841	3075048	1690551	2366455	1408533

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various employer characteristics, including the log hourly wages and the shares of groups by education, age, occupation, part-time and temporary contracts. It also includes the total number of employees observed in each sample.

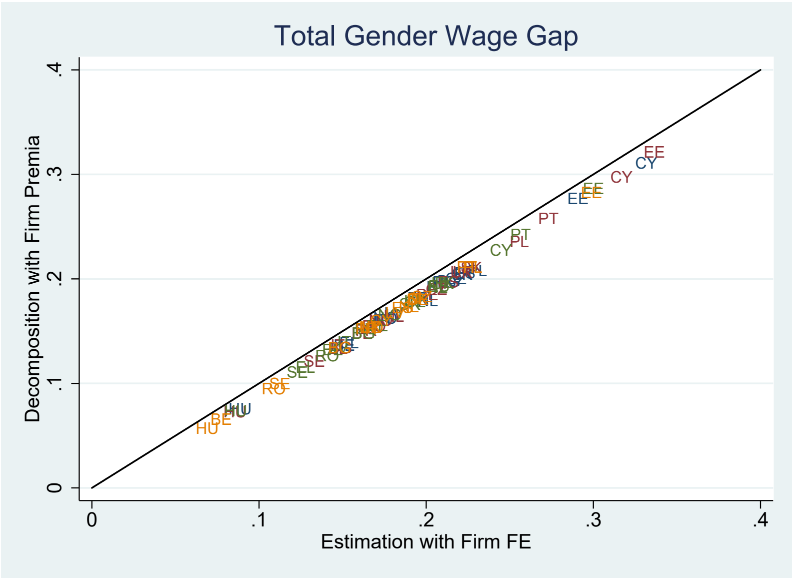
Table A9: Descriptive Statistics for various samples of Employers in SES (2014)

	(1)	(2)	(3)	(4)	(5)	(6)
	Original Data		**Cleaned Data (1 man & woman)**		**Cleaned Data (5 men & women)**	
	Males	Females	Males	Females	Males	Females
Log Hourly Wage	2.927	2.733	2.993	2.766	3.119	2.858
Primary education (%)	0.094	0.097	0.090	0.099	0.082	0.105
Secondary education (%)	0.687	0.708	0.668	0.701	0.629	0.672
Tertiary education (%)	0.218	0.195	0.243	0.201	0.289	0.223
Age 20-29 (%)	0.168	0.244	0.167	0.242	0.163	0.239
Age 30-39 (%)	0.235	0.224	0.236	0.223	0.244	0.230
Age 40-49 (%)	0.280	0.244	0.281	0.245	0.285	0.245
Age 50-59 (%)	0.257	0.238	0.258	0.240	0.256	0.241
Age 60-65 (%)	0.061	0.050	0.059	0.050	0.052	0.046
Managers (%)	0.040	0.024	0.039	0.023	0.040	0.020
Professionals (%)	0.122	0.108	0.143	0.112	0.183	0.130
Technicians (%)	0.177	0.205	0.195	0.201	0.216	0.203
Clerks (%)	0.130	0.334	0.149	0.350	0.183	0.354
Service workers (%)	0.054	0.152	0.054	0.126	0.041	0.078
Craft (%)	0.272	0.048	0.225	0.049	0.166	0.054
Operators (%)	0.144	0.059	0.135	0.064	0.118	0.080
Elementary (%)	0.062	0.071	0.060	0.074	0.054	0.081
Part Time (%)	0	0	0	0	0	0
Temporary Contract (%)	0.083	0.113	0.089	0.118	0.095	0.131
Number of employees	3068910	1717847	2757532	1628547	2117269	1345774

Notes: The table compares the data before and after cleaning with respect to requirements mentioned in the text, once with requiring 1 man and 1 woman per firm, and once with observing 5 men and 5 women per firm. The table compares various employer characteristics, including the log hourly wages and the shares of groups by education, age, occupation, part-time and temporary contracts. It also includes the total number of employees observed in each sample.

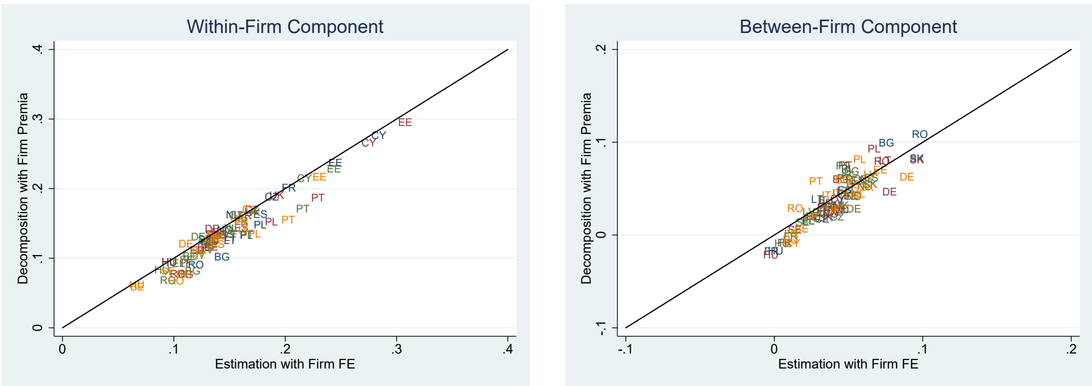
3.2 Comparison across Methods

Figure B1: Comparison Gender Wage Gap across Methods



This plot compares the total gender wage gap using the decomposition method by Card et al. (2016) and with firm-fixed effects similar to Barth et al. (2016) and Hara (2018). It shows that the estimated gender wage gaps are equivalent across both estimation methods.

Figure B2: Comparison of Gender Wage Gap Components across Methods



(a) Within-Firm Component (b) Between-Firm Components

This figure compares the within-firm and between-firm component of the gender wage gap using the decomposition method by Card et al. (2016) and with firm-fixed effects similar to Barth et al. (2016) and Hara (2018). For a comparison of the within-firm component, we aggregate the individual firm-fixed effects. It shows that the estimated components of the gender wage gaps are equivalent across both estimation methods.

3.3 Benchmark Decomposition Tables

Table C1: Comparison Firm-Fixed Effects by Gender (Normalization Low-Pay)

Country	(1) 2002	(2)	(3) 2006	(4)	(5) 2010	(6)	(7) 2014	(8)
	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F
BE	-.405	-.449	-.417	-.476	-.251	-.278	-.229	-.219
BG	-.492	-.541	-.389	-.422	-.468	-.516	-.418	-.469
CY	-.179	-.453	-.132	-.375	-.125	-.312	-.301	-.366
CZ	-.274	-.399	-.323	-.404	-.302	-.39	-.297	-.4
DE			-.41	-.509	-.392	-.46	-.415	-.486
EE	-.574	-.701	-.596	-.75	-.48	-.59	-.463	-.587
EL	-.266	-.326	-.335	-.374	-.36	-.398		
ES	-.349	-.44	-.339	-.425	-.305	-.395	-.334	-.42
FR	-.272	-.362	-.258	-.351	-.272	-.342	-.287	-.358
HU	-.519	-.524	-.532	-.556	-.473	-.502	-.428	-.457
IT	-.342	-.388	-.34	-.385	-.355	-.414	-.241	-.329
LT	-.57	-.611	-.551	-.624	-.394	-.509	-.378	-.471
LV	-.645	-.67	-.641	-.683	-.519	-.583	-.433	-.513
NL	-.302	-.31	-.285	-.366	-.299	-.363	-.273	-.325
NO	-.374	-.358	-.321	-.348	-.334	-.341	-.297	-.337
PL	-.423	-.536	-.422	-.524	-.427	-.507	-.431	-.507
PT	-.266	-.439	-.263	-.448	-.222	-.376	-.238	-.344
RO	-.619	-.647	-.598	-.641	-.547	-.569	-.507	-.564
SE			-.365	-.401	-.328	-.354	-.371	-.339
SK	-.347	-.432	-.288	-.421	-.285	-.403	-.341	-.418
UK			-.421	-.484	-.506	-.563	-.513	-.564

Notes: The table compares the gender-specific firm-fixed effects obtained from equation (3.2). In order to obtain a lower-bound estimate of the within-firm component, the female premium has to be smaller than the male premium within the group it is normalized by. The average fixed effects are shown for firms which are paying average wages below , which is equal to 2/3 of the median pay.

Table C2: Firm Premia and Contribution of each Component to the Gender Wage Gap (2002)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.118	.269	.229	.039	-.002	.009	.031	.041
BG	.201	.474	.352	.122	.082	.054	.069	.04
CY	.312	.076	.054	.023	.055	.018	.005	-.033
CZ	.19	.166	.155	.011	.002	.028	-.018	.009
EE	.284	.415	.325	.09	.035	.036	.054	.055
EL	.138	.182	.158	.024	.019	.003	.021	.004
ES	.202	.297	.239	.059	.035	.028	.03	.024
FR	.181	.116	.137	-.021	-.03	.004	-.025	.009
HU	.096	.449	.377	.072	-.012	-.012	.084	.084
IT	.153	.249	.194	.054	.039	.037	.018	.015
LT	.18	.444	.347	.097	.027	.02	.077	.07
LV	.164	.575	.453	.123	.014	.008	.114	.108
NL	.142	.179	.134	.045	.019	.023	.022	.026
NO	.142	.157	.113	.045	.005	.007	.037	.04
PL	.208	.342	.272	.071	.055	.027	.043	.015
PT	.215	.227	.226	.001	.046	.035	-.034	-.046
RO	.198	.541	.397	.144	.094	.085	.059	.05
SK	.192	.235	.169	.066	.075	.075	-.009	-.009

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table C3: Firm Premia and Contribution of each Component to the Gender Wage Gap (2006)

Country	(1)	(2) Means of Firm Effects	(3)	(4)	(5) Between	(6)	(7) Within	(8)
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.131	.228	.195	.033	.022	.01	.023	.011
BG	.136	.393	.303	.09	.048	.023	.067	.042
CY	.3	.105	.072	.033	.035	.024	.009	-.002
CZ	.183	.192	.169	.023	.014	.041	-.018	.009
DE	.149	.309	.274	.035	.028	.055	-.02	.006
EE	.321	.435	.346	.089	.018	.028	.061	.071
EL	.136	.236	.201	.035	.029	.016	.019	.006
ES	.192	.268	.214	.053	.036	.029	.024	.017
FR	.142	.101	.117	-.017	-.016	.004	-.021	-.001
HU	.098	.456	.398	.058	-.014	-.011	.069	.072
IT	.128	.246	.206	.04	.021	.023	.017	.019
LT	.232	.483	.337	.146	.076	.054	.092	.07
LV	.169	.537	.441	.096	.043	-.003	.098	.053
NL	.149	.204	.156	.048	.026	.031	.017	.022
NO	.138	.16	.111	.048	.003	.014	.034	.045
PL	.243	.337	.239	.099	.074	.044	.055	.024
PT	.266	.22	.196	.025	.036	.045	-.021	-.011
RO	.156	.518	.412	.106	.067	.062	.044	.04
SE	.111	.197	.165	.032	-.005	-.002	.034	.037
SK	.206	.239	.173	.066	.069	.093	-.028	-.003
UK	.158	.249	.245	.004	0	.003	.001	.004

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table C4: Firm Premia and Contribution of each Component to the Gender Wage Gap (2010)

Country	(1)	(2) Means of Firm Effects	(3)	(4)	(5) Between	(6)	(7) Within	(8)
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.1	.144	.113	.031	.014	.016	.015	.017
BG	.156	.421	.323	.098	.054	.032	.065	.044
CY	.235	.108	.091	.017	.03	.009	.008	-.013
CZ	.172	.163	.148	.015	.014	.046	-.031	0
DE	.119	.287	.258	.029	.006	.042	-.013	.023
EE	.297	.341	.235	.106	.046	.053	.052	.06
EL	.114	.242	.222	.02	.028	.006	.014	-.008
ES	.183	.245	.193	.053	.037	.039	.014	.016
FR	.137	.112	.123	-.011	-.019	0	-.011	.008
HU	.113	.389	.338	.051	-.014	.006	.045	.065
IT	.111	.226	.213	.013	-.007	.006	.007	.02
LT	.221	.286	.216	.069	.032	.036	.033	.037
LV	.162	.42	.351	.069	.026	-.013	.083	.043
NL	.142	.201	.151	.05	.028	.028	.022	.022
NO	.143	.186	.125	.061	.011	.025	.036	.049
PL	.203	.343	.262	.082	.05	.037	.045	.032
PT	.247	.219	.169	.05	.027	.032	.019	.023
RO	.131	.485	.388	.097	.059	.033	.064	.038
SE	.101	.177	.142	.034	0	.005	.03	.034
SK	.175	.218	.164	.054	.041	.069	-.015	.013
UK	.156	.39	.351	.039	-.003	.01	.029	.043

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table C5: Firm Premia and Contribution of each Component to the Gender Wage Gap (2014)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.044	.117	.117	0	-.004	.001	-.001	.004
BG	.141	.394	.314	.081	.045	.03	.051	.036
CY	.174	.16	.135	.024	.005	-.003	.027	.019
CZ	.182	.162	.144	.018	.018	.055	-.036	.001
DE	.144	.32	.269	.051	.038	.064	-.013	.013
EE	.294	.31	.226	.084	.058	.053	.031	.027
ES	.165	.25	.218	.032	.027	.024	.008	.005
FR	.142	.141	.129	.012	-.011	.011	.001	.023
HU	.12	.359	.294	.065	.005	.012	.053	.06
IT	.17	.171	.133	.038	.03	.024	.013	.007
LT	.196	.273	.207	.066	.035	.024	.042	.031
LV	.209	.354	.262	.092	.086	.032	.06	.006
NL	.123	.177	.147	.03	.018	.034	-.004	.012
NO	.134	.205	.147	.059	.013	.027	.032	.046
PL	.219	.34	.246	.094	.062	.042	.053	.032
PT	.21	.219	.188	.031	.012	.01	.021	.019
RO	.101	.463	.414	.049	.022	-.009	.058	.027
SE	.089	.203	.178	.026	-.001	.006	.02	.026
SK	.178	.234	.179	.055	.036	.06	-.005	.018
UK	.117	.42	.38	.04	-.003	.004	.036	.043

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

3.4 Robustness Analysis: Subsample with 5 Men and 5 Women per Firm

Table D1: Returns to worker characteristics for subsample of firms with at least 5 employees of each gender

	(1) 2002	(2) 2006	(3) 2010	(4) 2014
Secondary education	0.200	0.194	0.188	0.179
Tertiary education	0.637	0.621	0.642	0.611
Age 30-39	0.122	0.135	0.145	0.152
Age 40-49	0.140	0.164	0.155	0.178
Age 50-59	0.179	0.151	0.130	0.146
Age 60-65	0.145	0.140	0.127	0.126
Tenure	0.036	0.038	0.030	0.026
Tenure^2	-0.001	-0.002	-0.001	-0.000
Constant	1.966	1.845	2.020	1.655

Notes: The table shows the means obtained from the Mincer wage regression in equation 3.1 for all years. The average returns to each characteristics is based on the country-specific estimations as every country might exhibit different returns to worker characteristics. Primary education and age group 20 to 29 constitute the reference group for each. Tenure is a continuous variable. The sample on which we estimate the returns to worker characteristics includes five men and women per firm. A large majority of the country-specific estimates are statistically significant on conventional levels.

Table D2: Comparison Firm-Fixed Effects by Gender (Normalization Low-Pay)

Country	(1) 2002	(2)	(3) 2006	(4)	(5) 2010	(6)	(7) 2014	(8)
	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F
BE	-.422	-.476	-.341	-.392	-.157	-.213	-.256	-.316
BG	-.509	-.574	-.418	-.464	-.486	-.526	-.438	-.478
CY	-.135	-.444	-.144	-.378	-.105	-.308	-.208	-.3
CZ	-.278	-.403	-.332	-.426	-.319	-.432	-.316	-.426
DE			-.419	-.526	-.396	-.481	-.41	-.497
EE	-.559	-.713	-.531	-.719	-.484	-.561	-.425	-.564
EL	-.197	-.3	-.292	-.368	-.27	-.389		
ES	-.273	-.381	-.286	-.399	-.237	-.351	-.308	-.414
FR	-.291	-.433	-.253	-.358	-.299	-.378	-.404	-.458
HU	-.57	-.557	-.582	-.606	-.496	-.545	-.444	-.488
IT	-.326	-.331	-.318	-.339	-.343	-.388	-.248	-.369
LT	-.595	-.66	-.537	-.596	-.355	-.535	-.351	-.388
LV	-.722	-.762	-.685	-.745	-.592	-.653	-.452	-.558
NL	-.306	-.297	-.28	-.317	-.266	-.326	-.193	-.231
NO	-.334	-.323	-.283	-.334	-.325	-.359	-.309	-.35
PL	-.409	-.534	-.408	-.514	-.43	-.51	-.445	-.522
PT	-.348	-.532	-.297	-.529	-.237	-.383	-.228	-.361
RO	-.666	-.719	-.601	-.643	-.558	-.583	-.543	-.583
SE					-.342	-.34	-.363	-.295
SK	-.351	-.439	-.303	-.44	-.294	-.414	-.346	-.444
UK					-.487	-.554	-.527	-.589

Notes: The table compares the gender-specific firm-fixed effects obtained from equation (3.2). In order to obtain a lower-bound estimate of the within-firm component, the female premium has to be smaller than the male premium within the group it is normalized by. The average fixed effects are shown for firms which are paying average wages below , which is equal to 2/3 of the median pay.

Table D3: Firm Premia and Contribution of each Component to the Gender Wage Gap (2002)

Country	(1)	(2) Means of Firm Effects	(3)	(4)	(5) Between	(6)	(7) Within	(8)
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.12	.257	.226	.032	.006	.021	.011	.025
BG	.216	.474	.355	.12	.09	.059	.06	.029
CY	.253	.075	.097	-.022	.007	-.008	-.014	-.028
CZ	.198	.173	.155	.018	.007	.031	-.012	.011
EE	.29	.397	.332	.065	.018	.023	.042	.047
EL	.141	.123	.117	.006	.011	.014	-.009	-.005
ES	.183	.243	.215	.028	.033	.036	-.008	-.005
FR	.163	.13	.151	-.021	-.005	.002	-.022	-.015
HU	.13	.483	.383	.1	.012	.005	.096	.088
IT	.148	.209	.166	.043	.031	.051	-.008	.011
LT	.242	.434	.315	.119	.066	.045	.074	.053
LV	.206	.642	.503	.139	.025	.017	.122	.114
NL	.126	.137	.104	.032	0	.029	.003	.032
NO	.144	.16	.112	.048	.009	.011	.037	.039
PL	.214	.33	.263	.067	.057	.03	.037	.01
PT	.196	.241	.27	-.03	.023	.033	-.063	-.053
RO	.222	.593	.445	.148	.116	.09	.058	.032
SK	.217	.254	.162	.091	.094	.095	-.004	-.003

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table D4: Firm Premia and Contribution of each Component to the Gender Wage Gap (2006)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.134	.236	.19	.046	.032	.031	.014	.014
BG	.15	.427	.337	.09	.048	.018	.072	.042
CY	.262	.115	.106	.009	.038	.019	-.01	-.028
CZ	.199	.208	.173	.035	.027	.049	-.014	.008
DE	.16	.324	.283	.041	.042	.068	-.027	-.002
EE	.295	.342	.302	.04	-.001	0	.04	.041
EL	.13	.213	.182	.031	.028	.047	-.015	.003
ES	.158	.229	.209	.02	.024	.029	-.009	-.004
FR	.142	.132	.131	.001	-.001	.013	-.012	.002
HU	.122	.464	.401	.064	.001	-.005	.069	.063
IT	.152	.234	.165	.069	.038	.04	.029	.03
LT	.263	.411	.28	.131	.069	.053	.077	.062
LV	.195	.583	.487	.097	.027	-.005	.101	.069
NL	.157	.199	.137	.062	.033	.023	.04	.029
NO	.141	.173	.121	.052	.009	.017	.035	.043
PL	.253	.318	.216	.102	.081	.053	.05	.022
PT	.269	.266	.255	.011	.034	.055	-.044	-.023
RO	.166	.518	.416	.102	.076	.055	.047	.026
SE	.114	.212	.168	.044	.003	.011	.032	.04
SK	.229	.27	.182	.088	.087	.105	-.018	.001
UK	.108	.146	.043	.104	0	0	.104	.104

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table D5: Firm Premia and Contribution of each Component to the Gender Wage Gap (2010)

Country	(1)	(2) Means of Firm Effects	(3)	(4)	(5) Between	(6)	(7) Within	(8)
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.099	.125	.1	.026	.015	.015	.011	.011
BG	.16	.454	.358	.096	.052	.026	.07	.044
CY	.235	.119	.107	.012	.026	.018	-.006	-.014
CZ	.184	.19	.172	.018	.014	.049	-.031	.004
DE	.133	.297	.267	.03	.021	.049	-.018	.009
EE	.29	.31	.226	.084	.032	.039	.045	.052
EL	.12	.226	.214	.011	.02	.019	-.008	-.009
ES	.158	.211	.196	.015	.02	.032	-.017	-.004
FR	.125	.123	.136	-.012	-.016	-.005	-.008	.004
HU	.151	.393	.334	.059	-.002	.015	.044	.06
IT	.132	.227	.204	.024	.005	.016	.007	.019
LT	.256	.239	.248	-.01	.01	.008	-.017	-.02
LV	.2	.467	.373	.094	.036	.004	.09	.058
NL	.135	.193	.141	.051	.03	.021	.031	.021
NO	.152	.206	.142	.064	.02	.028	.036	.045
PL	.216	.334	.248	.086	.06	.05	.036	.026
PT	.261	.238	.181	.058	.042	.056	.001	.015
RO	.129	.479	.395	.083	.053	.031	.052	.031
SE	.101	.184	.142	.042	.008	.012	.031	.034
SK	.194	.236	.165	.071	.051	.079	-.008	.021
UK	.127	.346	.324	.022	-.029	-.023	.045	.051

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table D6: Firm Premia and Contribution of each Component to the Gender Wage Gap (2014)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.048	.094	.09	.004	.003	.007	-.003	.001
BG	.154	.388	.303	.085	.047	.038	.047	.038
CY	.182	.179	.151	.028	.009	.001	.027	.019
CZ	.197	.199	.169	.03	.015	.053	-.024	.015
DE	.156	.337	.284	.053	.051	.07	-.017	.002
EE	.31	.289	.208	.081	.061	.059	.022	.02
ES	.152	.241	.227	.014	.015	.024	-.01	-.001
FR	.104	.181	.193	-.012	-.009	0	-.012	-.003
HU	.156	.37	.288	.082	.012	.017	.065	.069
IT	.17	.131	.115	.015	.032	.029	-.013	-.016
LT	.235	.249	.177	.072	.025	.033	.039	.046
LV	.221	.362	.273	.09	.068	.021	.069	.022
NL	.105	.148	.103	.046	.032	.037	.009	.014
NO	.144	.221	.157	.064	.022	.031	.032	.041
PL	.232	.33	.233	.097	.068	.057	.04	.029
PT	.213	.232	.193	.039	.033	.034	.005	.006
RO	.113	.482	.418	.064	.031	.016	.048	.033
SE	.097	.209	.175	.034	.004	.011	.023	.03
SK	.207	.258	.186	.072	.054	.071	0	.018
UK	.059	.401	.398	.003	-.023	-.041	.045	.027

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table D7: Robustness Analysis - Average Firm Premia (Subsample 5 Men and 5 Women)

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	0.110***	-0.045***	0.034***	0.068***	0.119***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region-Industry Agreement	0.135***	-0.012	0.012**	0.030***	0.174***
	(0.000)	(0.322)	(0.047)	(0.000)	(0.000)
Enterprise agreement	0.115***	-0.040***	0.058***	0.069***	0.110***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local Unit Agreement	0.169***	-0.052*	0.025	0.040	0.183**
	(0.000)	(0.080)	(0.244)	(0.710)	(0.017)
Other agreement	0.013	0.028	-0.063***	0.174***	0.132***
	(0.404)	(0.126)	(0.000)	(0.000)	(0.006)
No agreement	0.210***	0.029***	0.082***	0.109***	0.126***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Firm Size					
50-249 Employees	0.036***	0.111***	0.037***	0.020***	0.071***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
250+ Employees	0.016***	0.219***	0.078***	0.076***	0.029
	(0.000)	(0.000)	(0.000)	(0.000)	(0.165)
Control					
Private	0.084***	-0.011*	0.079***	0.098***	0.087***
	(0.000)	(0.087)	(0.000)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	-0.001***	0.000	0.000***	-0.000***	-0.001***
	(0.000)	(0.123)	(0.000)	(0.006)	(0.000)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.006***	0.004***	0.003***	0.007***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.004***	0.003***	0.002***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clerks (%)	0.001***	0.001***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Executives (%)	0.000*	0.000	0.000	-0.000	0.000
	(0.058)	(0.709)	(0.688)	(0.285)	(0.183)
Female among White Collars (%)	-0.001***	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Clerks (%)	0.000***	-0.000***	-0.000***	-0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.064)	(0.000)
Female among Blue Collars (%)	-0.000***	-0.000*	-0.000***	-0.000***	-0.000***
	(0.000)	(0.055)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%)	-0.008***	-0.008***	-0.008***	-0.009***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%F-%M)	-0.001***	0.000	-0.000	-0.000*	-0.001***
	(0.000)	(0.151)	(0.549)	(0.055)	(0.000)
Observations	128189	18626	38394	34198	36971
R^2	0.43	0.43	0.57	0.46	0.44

Notes: The dependent variable is the average firm premia (weighted by employment shares) based on estimated firm-fixed effects for each gender. The firm premia are normalized by low-pay firms from the sample including 5 men and 5 women per firm. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table D8: Within-Firm Gender Wage Gap in Firm Premia

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	-1.741***	-1.360**	-0.290	-0.308	-1.882***
	(0.000)	(0.020)	(0.377)	(0.141)	(0.000)
Region-Industry Agreement	-2.213***	0.592	-1.107**	0.079	-2.742***
	(0.000)	(0.422)	(0.014)	(0.839)	(0.000)
Enterprise agreement	-2.022***	-3.066***	-1.132***	-0.202	-3.078***
	(0.000)	(0.000)	(0.001)	(0.410)	(0.000)
Local Unit Agreement	-0.431	-4.933***	0.410	-5.570	0.344
	(0.871)	(0.007)	(0.797)	(0.442)	(0.952)
Other agreement	-3.816***	-4.731***	0.834	2.569	-0.790
	(0.000)	(0.000)	(0.173)	(0.350)	(0.825)
No agreement	-1.213**	-3.843***	-0.514	-1.148	-3.861**
	(0.027)	(0.000)	(0.263)	(0.381)	(0.019)
Firm Size					
50-249 Employees	-0.682***	2.230***	1.485***	-0.732***	2.410
	(0.000)	(0.000)	(0.000)	(0.000)	(0.118)
250+ Employees	0.408**	3.140***	1.130***	-1.200***	3.910**
	(0.017)	(0.000)	(0.000)	(0.000)	(0.011)
Control					
Private	3.362***	0.891**	2.821***	2.464***	3.736***
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	-0.026***	-0.009	-0.002	-0.001	-0.035***
	(0.000)	(0.188)	(0.647)	(0.854)	(0.000)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.257***	0.163***	0.067***	0.231***	0.333***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.049***	0.040***	0.002	0.017***	0.067***
	(0.000)	(0.000)	(0.570)	(0.000)	(0.000)
Clerks (%)	0.037***	-0.003	0.014***	0.062***	0.038***
	(0.000)	(0.682)	(0.003)	(0.000)	(0.000)
Female among Executives (%)	-0.046***	-0.069***	-0.050***	-0.053***	-0.045***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among White Collars (%)	-0.015***	0.017***	0.020***	-0.035***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Clerks (%)	0.017***	0.029***	0.038***	0.027***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Blue Collars (%)	0.047***	0.018***	-0.006*	0.057***	0.044***
	(0.000)	(0.001)	(0.085)	(0.000)	(0.000)
Low Pay Earners (%)	-0.019***	-0.096***	-0.085***	-0.031***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Low Pay Earners (%F-%M)	0.372***	0.378***	0.376***	0.365***	0.374***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	128189	18626	38394	34198	36971
R^2	0.22	0.25	0.22	0.24	0.22

Notes: The dependent variable is the difference in firm premia (male minus female) based on estimated firm-fixed effects for each gender. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table D9: Between-Firm Gender Wage Gap in Firm Premia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male Effects	Expenditure (Total)	Expenditure (Cash)	Expenditure (Services)	Expenditure (Tax)	Length Maternity Leave	Length Paternity Leave	Childcare Enrollment 0-2 (%)	Childcare Enrollment 3-5 (%)
Total	-1.526***	-1.835***	-2.232***	-0.591	0.015**	-0.023	-0.076***	-0.106***
	(0.000)	(0.002)	(0.001)	(0.673)	(0.017)	(0.608)	(0.000)	(0.004)
20-29	-0.801**	-1.049*	-0.441	-2.656**	0.005	0.042	0.023	0.031
	(0.035)	(0.071)	(0.506)	(0.020)	(0.370)	(0.289)	(0.279)	(0.394)
30-39	-1.139*	-0.701	-2.418***	-0.381	0.034***	-0.041	-0.103***	-0.162***
	(0.053)	(0.356)	(0.004)	(0.833)	(0.000)	(0.472)	(0.000)	(0.000)
40-49	-1.863***	-1.946***	-2.898***	-0.195	0.014*	-0.052	-0.121***	-0.173***
	(0.000)	(0.003)	(0.000)	(0.906)	(0.054)	(0.329)	(0.000)	(0.000)
50-59	-1.737***	-2.540***	-2.560***	-0.580	0.000	-0.054	-0.061**	-0.088**
	(0.000)	(0.000)	(0.001)	(0.703)	(0.970)	(0.303)	(0.027)	(0.044)
60-64	-4.028***	-6.043***	-1.991	-5.311*	-0.012	-0.028	-0.059	-0.101
	(0.000)	(0.000)	(0.204)	(0.084)	(0.447)	(0.798)	(0.216)	(0.143)
Female Effects								
Total	-1.361***	-1.686***	-2.467***	1.461	0.018***	-0.042	-0.081***	-0.099**
	(0.006)	(0.010)	(0.001)	(0.344)	(0.009)	(0.418)	(0.001)	(0.026)
20-29	-0.236	-0.171	-0.508	-1.127	0.011*	0.011	0.013	0.015
	(0.530)	(0.777)	(0.456)	(0.317)	(0.062)	(0.792)	(0.572)	(0.714)
30-39	-0.968	-0.231	-2.529***	1.453	0.038***	-0.070	-0.109***	-0.168***
	(0.139)	(0.780)	(0.005)	(0.465)	(0.000)	(0.278)	(0.000)	(0.001)
40-49	-1.826***	-2.327***	-3.178***	2.735	0.017*	-0.060	-0.132***	-0.158***
	(0.005)	(0.007)	(0.001)	(0.176)	(0.062)	(0.377)	(0.000)	(0.006)
50-59	-2.047***	-3.385***	-3.011***	1.420	-0.003	-0.045	-0.064**	-0.053
	(0.000)	(0.000)	(0.001)	(0.397)	(0.716)	(0.459)	(0.035)	(0.314)
60-64	-3.322***	-6.353***	-1.404	-1.467	-0.012	-0.020	-0.039	-0.063
	(0.000)	(0.000)	(0.353)	(0.629)	(0.415)	(0.851)	(0.404)	(0.377)
Observations	46	63	63	46	54	54	51	45

Notes: The dependent variable is the between-firm component, the upper panel makes use of the male effects while the lower panel makes use of female effects. The table shows correlations between the two different between-firm components and various OECD indicators regarding public policies for families and children. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

3.5 Robustness Analysis: Normalization with Hotel & Restaurant Industry

Table E1: Comparison Firm-Fixed Effects by Gender (Normalization Hotel & Restaurants)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2002		2006		2010		2014	
	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F	Ψ^M	Ψ^F
BE	-.22	-.315	-.204	-.271	-.112	-.163	-.094	-.143
BG	-.187	-.207	-.168	-.217	-.158	-.219	-.097	-.149
CY	.146	-.033	.007	-.167	.033	-.146	-.024	-.169
CZ	-.003	-.164	-.083	-.248	-.071	-.226	-.088	-.251
DE			-.245	-.346	-.236	-.356	-.266	-.353
EE	-.204	-.326	-.192	-.397	-.13	-.27	-.103	-.278
EL	-.011	-.102	-.063	-.142	-.07	-.118		
ES	-.082	-.193	-.057	-.163	-.049	-.149	-.011	-.121
FR	-.059	-.189	.022	-.092	-.071	-.161	-.078	-.182
HU	-.256	-.294	-.169	-.21	-.213	-.278	-.186	-.279
IT	-.125	-.197	-.119	-.168	-.095	-.171	-.073	-.198
LT	-.317	-.321	-.29	-.371	-.194	-.218	-.181	-.242
LV	-.215	-.247	-.236	-.292	-.045	-.133	.014	-.078
NL	-.092	-.235	-.128	-.28	-.134	-.262	-.1	-.224
NO	-.091	-.177	-.114	-.191	-.129	-.215	-.159	-.229
PL	-.097	-.213	-.078	-.192	-.109	-.241	-.099	-.234
PT	-.01	-.169	.031	-.173	-.025	-.215	-.045	-.208
RO	-.194	-.28	-.168	-.225	-.233	-.283	-.243	-.267
SE			-.123	-.192	-.086	-.162	-.102	-.149
SK	-.107	-.161	-.1	-.227	-.072	-.213	-.076	-.218
UK			-.204	-.318	-.266	-.36	-.267	-.361

Notes: The table compares the gender-specific firm-fixed effects obtained from equation (3.2). In order to obtain a lower-bound estimate of the within-firm component, the female premium has to be smaller than the male premium within the group it is normalized by. The average fixed effects are shown for firms in the sector as it is considered a low-wage industry.

Table E2: Firm Premia and Contribution of each Component to the Gender Wage Gap (2002)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.118	.249	.226	.023	-.002	.009	.014	.024
BG	.201	.272	.092	.181	.082	.054	.127	.099
CY	.312	-.015	-.149	.133	.055	.018	.116	.078
CZ	.19	.074	.046	.029	.002	.028	0	.027
EE	.284	.326	.164	.162	.035	.036	.127	.127
EL	.138	.064	.018	.047	.019	.003	.044	.027
ES	.202	.152	.062	.091	.035	.028	.063	.056
FR	.181	.121	.07	.051	-.03	.004	.047	.081
HU	.096	.296	.238	.058	-.012	-.012	.07	.07
IT	.153	.176	.096	.08	.039	.037	.044	.041
LT	.18	.393	.217	.176	.027	.02	.156	.149
LV	.164	.288	.156	.132	.014	.008	.124	.117
NL	.142	.128	.129	-.001	.019	.023	-.025	-.02
NO	.142	.13	.074	.056	.005	.007	.049	.051
PL	.208	.174	.082	.093	.055	.027	.065	.037
PT	.215	.102	.046	.056	.046	.035	.021	.01
RO	.198	.274	.162	.112	.094	.085	.027	.018
SK	.192	.189	.052	.138	.075	.075	.062	.063

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table E3: Firm Premia and Contribution of each Component to the Gender Wage Gap (2006)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.131	.236	.173	.063	.022	.01	.053	.041
BG	.136	.227	.14	.087	.048	.023	.064	.039
CY	.3	.124	-.002	.125	.035	.024	.102	.09
CZ	.183	.149	.132	.018	.014	.041	-.023	.003
DE	.149	.284	.237	.047	.028	.055	-.008	.019
EE	.321	.347	.231	.116	.018	.028	.088	.098
EL	.136	.115	.059	.057	.029	.016	.041	.028
ES	.192	.129	.042	.086	.036	.029	.057	.051
FR	.142	.028	.001	.028	-.016	.004	.023	.043
HU	.098	.21	.152	.058	-.014	-.011	.069	.073
IT	.128	.161	.081	.08	.021	.023	.057	.059
LT	.232	.387	.236	.151	.076	.054	.097	.075
LV	.169	.312	.199	.113	.043	-.003	.116	.07
NL	.149	.169	.172	-.003	.026	.031	-.034	-.03
NO	.138	.151	.09	.061	.003	.014	.047	.058
PL	.243	.167	.038	.129	.074	.044	.085	.054
PT	.266	.078	.016	.062	.036	.045	.017	.026
RO	.156	.232	.133	.099	.067	.062	.038	.033
SE	.111	.155	.114	.041	-.005	-.002	.043	.047
SK	.206	.182	.103	.078	.069	.093	-.015	.01
UK	.158	.266	.222	.044	0	.003	.042	.045

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table E4: Firm Premia and Contribution of each Component to the Gender Wage Gap (2010)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.1	.14	.091	.049	.014	.016	.034	.035
BG	.156	.227	.131	.096	.054	.032	.063	.042
CY	.235	.07	.014	.056	.03	.009	.047	.027
CZ	.172	.136	.118	.018	.014	.046	-.028	.004
DE	.119	.266	.267	-.002	.006	.042	-.044	-.008
EE	.297	.263	.105	.157	.046	.053	.104	.112
EL	.114	.119	.052	.066	.028	.006	.06	.038
ES	.183	.119	.036	.083	.037	.039	.044	.046
FR	.137	.123	.076	.047	-.019	0	.047	.066
HU	.113	.262	.214	.048	-.014	.006	.042	.062
IT	.111	.13	.096	.034	-.007	.006	.028	.041
LT	.221	.291	.094	.197	.032	.036	.161	.165
LV	.162	.116	.042	.074	.026	-.013	.088	.048
NL	.142	.169	.155	.014	.028	.028	-.014	-.014
NO	.143	.168	.112	.057	.011	.025	.032	.045
PL	.203	.184	.113	.071	.05	.037	.034	.022
PT	.247	.125	.067	.057	.027	.032	.025	.03
RO	.131	.286	.205	.081	.059	.033	.048	.022
SE	.101	.116	.092	.025	0	.005	.02	.024
SK	.175	.144	.109	.034	.041	.069	-.035	-.007
UK	.156	.327	.264	.063	-.003	.01	.053	.066

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table E5: Firm Premia and Contribution of each Component to the Gender Wage Gap (2014)

Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Means of Firm Effects			**Between**		**Within**	
	Residual GWG	Male premium	Female premium	GWG in firm premiums	Using Male Effects	Using Female Effects	Using Male Distribution	Using Female Distribution
BE	.044	.106	.111	-.005	-.004	.001	-.006	-.001
BG	.141	.159	.07	.089	.045	.03	.059	.044
CY	.174	.106	.077	.029	.005	-.003	.032	.024
CZ	.182	.157	.139	.018	.018	.055	-.036	.001
DE	.144	.307	.25	.057	.038	.064	-.007	.019
EE	.294	.236	.116	.12	.058	.053	.066	.062
ES	.165	.074	.019	.055	.027	.024	.031	.028
FR	.142	.131	.092	.039	-.011	.011	.028	.05
HU	.12	.233	.206	.027	.005	.012	.016	.022
IT	.17	.138	.093	.045	.03	.024	.021	.015
LT	.196	.266	.131	.135	.035	.024	.111	.1
LV	.209	.077	-.04	.117	.086	.032	.085	.031
NL	.123	.132	.133	-.001	.018	.034	-.035	-.019
NO	.134	.197	.133	.064	.013	.027	.037	.052
PL	.219	.18	.097	.083	.062	.042	.041	.021
PT	.21	.136	.089	.047	.012	.01	.036	.035
RO	.101	.284	.208	.076	.022	-.009	.085	.054
SE	.089	.129	.086	.042	-.001	.006	.036	.043
SK	.178	.147	.111	.036	.036	.06	-.024	0
UK	.117	.314	.291	.023	-.003	.004	.019	.026

Notes: The table provides information by country on the firm premia by gender, the wage gap and the size of the between- and within-firm component. Column (1) presents the residual gender wage gap, and columns (2) and (3) show the average of the male and female firm premium, respectively. Column (4) is the difference between the first two columns, and constitutes the firms' contribution to the gender wage gap. This wage gap is then decomposed into a between- and within-firm component, shown in Columns (5) and (6), and (7) and (8), respectively. The decomposition is based on equations (3.3) and (3.4) and uses male or female effects for the between-firm component and the male or female distribution for the within-component. The sum of columns (5) and (8), and columns (6) and (7) is equal to Column (4).

Table E6: Robustness Analysis - Average Firm Premia (Normalization Hotel & Restaurant Sector)

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	0.142***	-0.034***	0.032***	0.074***	0.162***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region-Industry Agreement	0.177***	-0.034***	0.047***	0.025***	0.229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Enterprise agreement	0.155***	-0.007	0.045***	0.074***	0.172***
	(0.000)	(0.253)	(0.000)	(0.000)	(0.000)
Local Unit Agreement	0.134***	-0.048***	0.024***	0.033**	0.139***
	(0.000)	(0.002)	(0.000)	(0.032)	(0.000)
Other agreement	0.073***	-0.001	-0.033***	0.091***	0.160***
	(0.000)	(0.948)	(0.000)	(0.000)	(0.000)
No agreement	0.196***	-0.005	0.081***	0.115***	0.163***
	(0.000)	(0.258)	(0.000)	(0.000)	(0.000)
Firm Size					
50-249 Employees	0.038***	0.081***	0.059***	0.048***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
250+ Employees	0.066***	0.117***	0.062***	0.104***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control					
Private	0.043***	-0.006	0.031***	0.047***	0.050***
	(0.000)	(0.148)	(0.000)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	0.000***	0.000***	0.000	-0.000**	0.001***
	(0.000)	(0.000)	(0.266)	(0.034)	(0.000)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.005***	0.004***	0.004***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.004***	0.002***	0.003***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clerks (%)	0.002***	0.001***	0.000***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Executives (%)	-0.000*	0.000***	-0.000***	-0.000***	-0.000
	(0.071)	(0.000)	(0.001)	(0.000)	(0.965)
Female among White Collars (%)	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***
	(0.000)	(0.003)	(0.002)	(0.000)	(0.000)
Female among Clerks (%)	0.000***	-0.000**	0.000***	0.000**	0.000***
	(0.000)	(0.047)	(0.000)	(0.037)	(0.000)
Female among Blue Collars (%)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%)	-0.006***	-0.007***	-0.008***	-0.008***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%F-%M)	-0.000***	0.000**	0.000***	-0.000***	-0.000***
	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)
Observations	413035	70918	118750	95955	127412
R^2	0.34	0.30	0.40	0.42	0.33

Notes: The dependent variable is the average firm premia (weighted by employment shares) based on estimated firm-fixed effects for each gender. The firm premia are normalized by firms in the hotel & restaurant industry. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table E7: Within-Firm Gender Wage Gap in Firm Premia

	(1) All years	(2) 2002	(3) 2006	(4) 2010	(5) 2014
Pay Agreement					
Industry Agreement	-1.085***	-1.061	-1.491**	-0.427**	-1.050***
	(0.000)	(0.105)	(0.020)	(0.045)	(0.000)
Region-Industry Agreement	-1.363***	0.319	-1.703**	-0.355	-1.979***
	(0.000)	(0.662)	(0.016)	(0.399)	(0.000)
Enterprise agreement	-1.608***	-2.045***	-1.614**	0.008	-2.153***
	(0.000)	(0.003)	(0.018)	(0.976)	(0.000)
Local Unit Agreement	-1.661*	-2.113	-1.766**	1.298	-5.245*
	(0.069)	(0.250)	(0.039)	(0.399)	(0.083)
Other agreement	-5.399***	-4.612***	-5.181***	0.382	-1.990
	(0.000)	(0.000)	(0.000)	(0.765)	(0.413)
No agreement	-2.365***	-2.186***	-4.074***	-0.078	-1.865
	(0.000)	(0.000)	(0.000)	(0.922)	(0.196)
Firm Size					
50-249 Employees	1.383***	1.419***	1.217***	1.322***	0.725
	(0.000)	(0.000)	(0.000)	(0.000)	(0.396)
250+ Employees	1.358***	0.106	-0.376	0.239	1.078
	(0.000)	(0.708)	(0.138)	(0.247)	(0.206)
Control					
Private	2.611***	3.099***	0.891	1.658***	2.740***
	(0.000)	(0.000)	(0.120)	(0.000)	(0.000)
Workforce Composition					
Temporary Contract (%)	-0.005**	-0.025***	-0.017***	-0.019***	-0.006
	(0.040)	(0.000)	(0.001)	(0.001)	(0.190)
Part-time (%)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Executives (%)	0.311***	0.226***	0.284***	0.352***	0.322***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White Collars (%)	0.055***	0.047***	0.040***	0.065***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clerks (%)	0.032***	-0.018***	-0.014**	0.087***	0.025***
	(0.000)	(0.001)	(0.018)	(0.000)	(0.000)
Female among Executives (%)	-0.166***	-0.140***	-0.199***	-0.109***	-0.184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among White Collars (%)	0.034***	0.041***	-0.004	-0.015***	0.046***
	(0.000)	(0.000)	(0.190)	(0.000)	(0.000)
Female among Clerks (%)	0.026***	0.068***	0.089***	0.034***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female among Blue Collars (%)	0.055***	0.032***	0.038***	0.065***	0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Pay Earners (%)	-0.011***	-0.092***	-0.083***	0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Low Pay Earners (%F-%M)	0.353***	0.272***	0.366***	0.352***	0.354***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	413035	70918	118750	95955	127412
R^2	0.22	0.16	0.23	0.24	0.22

Notes: The dependent variable is the difference in firm premia (male minus female) based on estimated firm-fixed effects for each gender. The sample includes firms with at least one man and one woman per firm. Sector, country and year-fixed effects are not shown. Firm observations are weighted. Robust standard errors are used. p-values are shown in brackets. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Chapter 4

Can labor market institutions mitigate the China syndrome? Evidence from European regional labor markets

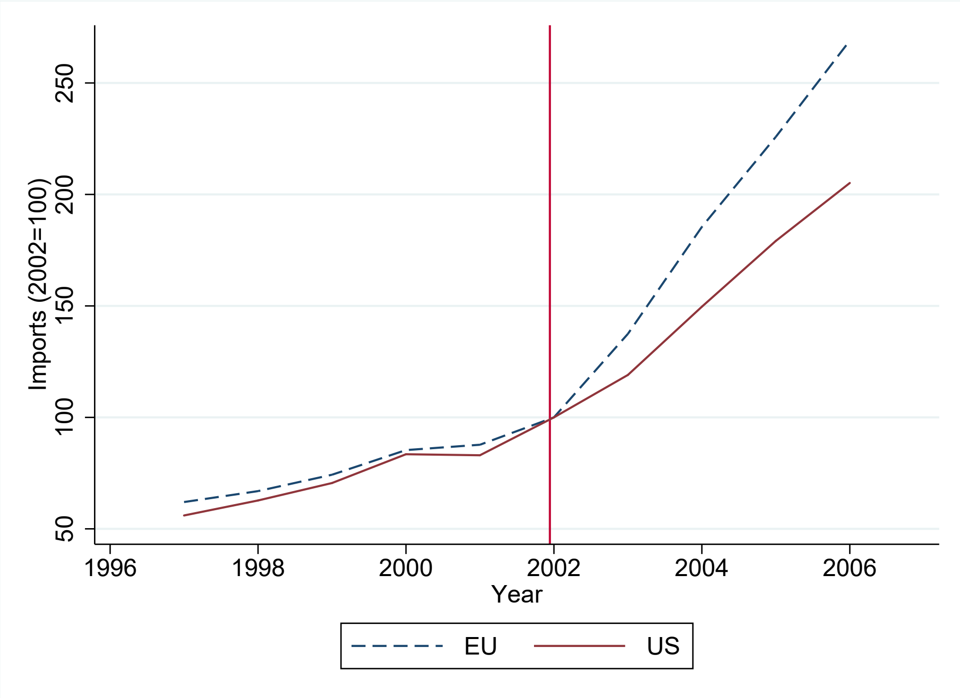
4.1 Introduction

The academic and public debate about the impact of trade with low-wage countries on labor markets in advanced economies received a boost in recent years. The discussion of the 1990s on this issue focused mainly on the wage impact of skilled versus unskilled workers, but no major impact was found. However, Wood (2018) argues that the debate ended prematurely and Krugman (2008) adds that the small effects found in the 1990s are not surprising given the low levels of trade between high- and low-wage countries at the time.

The share of trade of European economies and the United States with low-income countries has been rising sharply in the period around the new millennium, which is largely due to China and its entry in the World Trade Organization (WTO). Figure 4.1 shows that Chinese export growth to Europe exceeds that of the United States since 2002. Autor et al. (2013) are the first to exploit supply-driven import exposure per worker in US local labor markets from China and to analyze the impact on manufacturing employment. Examples of other single-country studies exploiting the same instrument are Donoso et al. (2015) for Spain and Balsvik et al. (2015) for Norway. All of these studies find a significant negative response of manufacturing employment when import competition from China is high. Both studies find different point estimates relative to Autor et al. (2013) for the adverse impact of Chinese import competition on manufacturing employment and hypothesize that this may be due to different labor market institutions.

This study contributes to this literature in two ways. First, the paper investigates whether labor market frictions modifies the impact of import competition from China on manufacturing employment shares by including an interaction term between import competition and labor market frictions. Standard economic theory predicts that high labor market frictions, specifically in the form of employment protection, reduces job flows as argued by Bertola and Rogerson (1997). More recently, Caliendo et al. (2019) implement

Figure 4.1: EU vs. US imports from China



The figure shows the increase in Chinese exports to the eight European countries under investigation and the United States. Aggregate bilateral trade flows are taken from the OECD International Merchandise Trade Statistics. They are originally measured in US Dollar, and here normalized to 100 in 2002 to present percentage growth over the time period 1997 to 2006. The vertical line represents the date of entry of China into the WTO on 11 December 2001.

labor market frictions in the form of sector-region reallocation costs for workers. Similarly, Dix-Carneiro (2014) also estimates large and heterogeneous sectoral reallocation costs for workers. Instead, this paper focuses on involuntary reallocation of employees caused by the local adoption of temporary contracts.

The second contribution is to investigate the response of other employment and non-employment alternatives due to Chinese import competition. The employment option implies working in another sector than manufacturing, and non-employment can be either unemployment or exiting the labor force. Caliendo et al. (2019) argue that other sectors, such as construction and services can expand due to access to cheaper intermediate inputs. Charles et al. (2016) argue that the housing boom, and hence employment in construction, masked the overall decline in job growth in the US. For Spain, Donoso et al. (2015) show that the employment reduction in the manufacturing sector was absorbed by other sectors, specifically construction. In terms of unemployment and labor force participation, Autor et al. (2013) find an increase in the former and decrease in the latter. Overall, the empirical evidence is mixed if any sector absorbs, and if yes, which sector absorbs the adverse impact of the trade shock on manufacturing.

The setup of the study is similar to other reduced-form analyses examining China's rise in world markets and how this affects various outcomes in Western countries. Bloom et al. (2016) examine firms in a panel of 12 European countries following the "value share" approach, which exploits *industry* level exposure to China compared to regional import exposure. To the author's knowledge, Colantone and Stanig (2017) are the first to consider regional import exposure in a multi-country setting. They investigate voting pattern changes conditional on import exposure, whereas this paper is concerned with labor market outcomes in various sectors, in particular employment shares over working-age population and hourly wages.

In order to answer the above-mentioned research questions, this paper relates changes in employment shares of manufacturing, services, construction, public services, the unemployment rate and labor force participation rate between 1997 until 2006 to exposure to supply-driven Chinese exports and labor market frictions on the NUTS 2 level for eight European economies, i.e. Austria, Belgium, France, Germany, Italy, Spain, Sweden and the United Kingdom. To identify the supply-driven component of imports from China, this paper follows Autor et al. (2013) by exploiting within-manufacturing composition in terms of employment on the regional level and by instrumenting for EU country imports using changes in imports of the US from China, similar to previous studies.

The paper develops two measures of regional labor market frictions based on the idea that employment protection differs for temporary and permanent jobs. The first measure accounts for the involuntary, i.e. because they could not find a permanent contract, flow from unemployment into temporary jobs relative to all unemployed. The second measure exploits the flows of temporary employed persons in the previous year to unemployment because the temporary contract expired, relative to all employed. Both measures are increasing with labor market frictions as they exemplify a higher use of temporary contracts as permanent contracts are associated with higher costs. In other words, temporary employment is linked to stronger employment protection legislation, therefore implying stronger frictions.

The identification strategy first acknowledges that, as import competition is an endogenous regressor, its interaction with regional labor market frictions is likely to be endogenous as well. However, Nizalova and Murtazashvili (2016) and Bun and Harrison (2018) show that the interaction term can be interpreted as exogenous once the main effect of the endogenous variable has been taken account of, and the OLS estimator of the interaction term is unbiased and consistent. Alternatively, the paper applies two further identification strategies, which encompass two first stage regressions, one for import competition and one for its interaction with labor market frictions. The two identification strategies differ in their instrument(s) for the interaction term: one follows Bun and Harrison (2018) in that it exploits the vector of second-order polynomials of the instrument and the control variables as instruments for the interaction term. The other one follows the empirical application of Aghion et al. (2005), who instrument for the interaction term of the endogenous regressor and the modifying variable with the interaction term of the instrument and the modifying variable. All identification strategies yield qualitatively equal results.

The results suggest that regional import competition per worker reduces manufacturing employment substantially and significantly in the eight European economies under investigation. An increase of $ 1,000 (in 2005 value) in import exposure per worker is related to a decline of 1.04 percentage points in the manufacturing employment share relative to the working-age population over a 5-year period in a regional labor market with average friction.[1] Irrespective of the measure, stronger labor market frictions tends to further decrease the manufacturing employment share. This finding shows that employment protection exacerbates the employment response in the manufacturing sector, which is in line with the hypothesis postulated in Balsvik et al. (2015) and Donoso et al. (2015).

To determine what happens to displaced workers affected adversely by rising import competition from China, this paper investigates other sectors and two non-employment rates. The paper runs the same empirical exercise with employment shares of services, the construction sector and non-market services. The empirical evidence suggests that workers reallocated to public services, including health and education, and tended to do the same with private services with rising labor market frictions, though noisily estimated. The construction sector, on the other hand, did not absorb the shock. In terms of non-employment responses, the unemployment rate did not change, if anything unemployment fell in regions more exposed to Chinese import competition. On the other hand, the labor force participation rate tends to drop, in particular with rising labor market frictions. However, these estimates are also statistically insignificant.

The results for hourly wages, which should be treated cautiously due to potential biases, do not react to Chinese import competition. One reason is that wage cuts are less likely in Europe compared to the United States, which could also explain the much higher adverse impact found on manufacturing employment shares. In Europe, employers cannot adjust wages downward, so they react stronger in terms of employment, whereas in the United States, employers can adjust along both margins.

The paper is structured as follows: Section 4.2 introduces the measure for regional import competition from China and the two measures of regional labor market friction. Section 4.3 discusses the identification strategies and presents the results. Section 4.4 concludes.

4.2 Regional indicators

To determine the causal effects of supply-driven Chinese exports and labor market institutions on regional labor market dynamics, the first crucial step is to establish suitable indicators. This section introduces the measure for import exposure per worker and its instrument. It continues to present both measures for regional labor market frictions based

[1] The 1.04 percentage points is an average over all six point estimates.

on how common the use of temporary contracts are. The section also describes the data used in the analysis and provides descriptive statistics.

4.2.1 Import competition

The construction of the index for import exposure per worker follows both Autor et al. (2013) in employing the start of period employment of manufacturing subsectors for regional variation of the instrument. The changes in EU country-specific imports from China are then instrumented with US imports, based on the modification of, among others, Colantone and Stanig (2017). Due to the same regional focus, i.e. NUTS 2 regions in Europe, the subdivision of the manufacturing sector further follows Colantone and Stanig (2017), i.e. both employment and trade data are determined on the 2-digit level of the manufacturing sector according to NACE Rev.1.1. The measure of import competition is constructed the following:

$$\Delta IPW_{rt}^{EU} = \sum_j \frac{L_{rjt}}{L_{cjt}} \frac{\Delta IMP_{cChinajt}}{L_{rt}}, \tag{4.1}$$

where ΔIPW_{rt}^{EU} is defined as the import exposure per worker in region r at time t using bilateral trade of the individual EU country with China. L_{rjt} is the number of employees in manufacturing subsector j in region r at the initial year of each 5-year period t, divided by the number of employees in manufacturing subsector j in the country c (L_{cjt}) in the respective year. This fraction computes the degree of specialization of subsector j in region r relative to the rest of the respective country, and simply reflects a regional weighting coefficient. This fraction is multiplied by the normalized change in real imports of manufacturing goods of the individual European country c from China in subsector j over period t ($\Delta IMP_{cChinajt}$). Normalization means that the real change in imports is divided by the number of workers in region r in the initial year of period t (L_{rt}), resulting in import exposure *per worker*.

Bilateral trade between the European economies and China bears the potential for endogeneity as imports could be correlated with domestic factors, instead the main interest is to isolate the supply-driven component of Chinese exports. The most important factor, which could potentially introduce a bias in the estimation, is industry-specific demand for Chinese goods. This bias would lead to an underestimate of the true effect of supply-driven imports from China. To circumvent this endogeneity bias, the instrument exploits the change in US imports for the change in EU imports by manufacturing subsector over the same period:

$$\Delta IPW_{rt}^{US} = \sum_j \frac{L_{rjt}}{L_{cjt}} \frac{\Delta IMP_{USChinajt}}{L_{rt}}, \tag{4.2}$$

The only difference between equations (4.1) and (4.2) is visible in the numerator of the second fraction, i.e. the destination country of exports from China differs. In equation (4.2), US imports are shown, but an alternative is to use other (advanced) destination countries. These additional countries are Australia, Canada, Korea, Japan and New Zealand. A second alternative is to consider only net exports (NPW), which is potentially more relevant for European countries compared to the United States because they have a less unbalanced trade deficit with China. However, only Germany sees a strong rise in exports to China over the time horizon considered in the analysis. Hence the results for net import exposure are expected to be similar to import exposure.

4.2.2 Regional labor market frictions

The two measures of labor market frictions in this paper exploit "involuntary" reallocations compared to voluntary reallocations in the recent literature investigating labor dynamics induced by trade shocks with general equilibrium models, e.g. Caliendo et al. (2019). Other studies also exploit typically voluntary reallocations to estimate reallocation costs using structural models, for example Dix-Carneiro (2014) and Artuç et al. (2010). However, Jolivet et al. (2006) present evidence that involuntary reallocations are forming a substantial part of total reallocations, in particular in high-turnover countries. Further, the aforementioned theoretical studies exploit reallocations between sectors, i.e. job-to-job transitions, and disregard involuntary transitions into unemployment or vice versa. In contrast to the aforementioned theoretical studies, more reallocations are implying stronger labor market frictions. This is simply due to their involuntary nature compared to the voluntary transitions used in these papers.

The basic idea of the two measures of labor market frictions the paper puts forward relies on (Boeri and Van Ours, 2013, Fig. 10.3) and Kalleberg (2000) arguing that higher employment protection legislation (EPL) for permanent contracts exhibits a strong positive relationship with the share of temporary workers. Strict EPL for open-ended contracts induces higher costs for employers in the cases of firing, hence job seekers may work under temporary contracts even though they prefer to work under permanent contracts. This means that the labor market cannot absorb job seekers into permanent contracts because of higher employment protection, i.e. the labor market is the more rigid the more employees work under temporary contracts.

One issue with labor market institutions is that they are typically enforced on the national level and do not vary by region. However, Boeri and Jimeno (2005) demonstrate that EPL is not uniformly enforced within an economy due to the various exemptions, e.g. for small companies below certain threshold of employees. For companies exempted from strict employment protection for permanent contracts, it is easier to hire and fire workers under permanent contracts because they face lower costs. Thus, this paper constructs both measures on the same level of regional variation as import competition induced by Chinese goods, and not on the more aggregate, national level. The only attempt to get insights into subnational differences of EPL is Hantzsche et al. (2018), but the authors take on a sectoral perspective, not a regional one.

To isolate those temporary contracts, which are due to strict employment protection legislation and not due to preferences of the employees, both measures of labor market frictions make use "involuntary" temporary contracts. The first measure exploits the flows from unemployment into a temporary job from one year to another conditional on that the unemployed could not find a permanent job. This measure of involuntary flows into temporary jobs is normalized by the number of unemployed in the previous year in order to account for the size of local unemployment, which would otherwise put a greater weight on larger regions:

$$RLMF_{rt}^{UE \rightarrow Temp.Job} = \frac{Flow_{rt}^{UE \rightarrow Temp.Job}}{UE_{rt-1}}, \tag{4.3}$$

This indicator measures the chance of an unemployed to enter a temporary contract despite his initial objective to find work under a permanent contract. It is assumed that the firm considers the costs to hand out an infinite-horizon contract to the worker as too high because its high employment protection, hence it only offers fixed-period jobs.

The second indicator reverses the direction of the flow, i.e. it looks at whether an individual entered unemployment in period t because a temporary ended. Hence, it measures how many temporary contracts were used the year before and did not result in further employment, may it be a permanent or a renewed temporary contract.[2] This is normalized by total employment in the previous period:

$$RLMF_{rt}^{Temp.Job \rightarrow UE} = \frac{Flow_{rt}^{Temp.Job \rightarrow UE}}{Employment_{rt-1}}, \tag{4.4}$$

Both measures highlight the use of "involuntary" temporary contracts, which are more commonly used if the regional labor market is rigid as permanent contracts are more expensive to the firm relative to temporary contracts. Hence, both indicator rise with regional labor market friction. Flows in both directions are roughly equal in absolute numbers, the normalization factors for each measure, i.e. denominators in both equations, differ strongly, both indicators are standardized for the empirical analysis. This allows for a more comparable interpretation of the results.

This paper argues that both measures of labor market frictions are exogenous to the trade shock from Chinese imports, even though a common concern is that labor market institutions are endogenous to globalization. It is often argued that trade openness erodes labor market standards. However, the empirical evidence is quite mixed on whether global-

[2] This measure may not also include a certain degree of skill mismatch between employee and employer as temporary contracts also allow for the screening of the quality of the match.

ization has an impact on labor market institutions, with results varying by labor market setting and with different country samples and identification strategies. They are summarized in Potrafke (2013), who in his analysis does not find any evidence that globalization impacts labor market institutions. Further, most studies focus on trade between advanced economies, which is due to the above-mentioned phenomenon that trade between advanced economies and developing countries did not occur until the rise of China in global commodity markets. To the author's knowledge, Häberli et al. (2012) is the only study examining how trade agreements between countries with different stages of economic development affect labor market institutions. The main finding is that trade between two advanced economies reduces institutional labor market standards, whereas trade between an advanced economy and developing countries does not impact the institutional setting of the importing country. For these reasons, the identification strategy treats the modifying variable, i.e. labor market friction, as exogenous to the supply-driven component of Chinese imports.

4.2.3 Data

This paper focuses on eight European economies, which include Austria, Belgium, France, Germany, Italy, Spain, Sweden and the United Kingdom between 1997 and 2006. These countries have been selected for two reasons. The first reason is that this paper concentrates on countries, which are likely to suffer from a direct impact of Chinese import competition. Cabral et al. (2018) show that Portugal only loses manufacturing employment due to the indirect effect of Chinese exports crowding out Portuguese exports. These indirect effects are occurring in European low-wage countries. This leads to the omission of all East European countries, Greece and Portugal. The second reason are data limitations on the remaining countries. The Netherlands and Denmark do not provide regional information in the EU LFS, which is the main data source to compute regional labor market frictions. The exclusion of Finland and Norway is based on the lack of employment data in the manufacturing subsectors previous to 2002. Finally, Luxembourg and Ireland are left out because they consist of only one and two, respectively, NUTS 2 regions, hence it does not allow for within-country identification. Analogous to previous studies, the time horizon is chosen to capture periods of the same length around China's entry into the WTO in 2001 and to predate the Great Financial Crisis (2007-2009).

Employment data for six sectors comes from the European Regional Database (ERD), and are aggregated to manufacturing, services, construction and private services.[3] The data is available on the NUTS 2 level, which comprises also the geographical degree of variation. The sectoral employment shares are computed relative to working-age population,

[3] Private services sector encompasses "wholesale, retail, transport, accommodation & food services, information and communication" and "financial & business services".

similar to previous studies investigating whether import competition from China affects manufacturing employment. The working-age population is restricted to the age from 20 to 64 and stems from Eurostat Regional Database. One main issue with this feature could be that this study, in contrast to Autor et al. (2013), exploits variation in administrative units instead of commuting zones. Administrative regions do not form closed labor markets in the same form, but comparing data on region of residence and region of work in the EU LFS exhibits that the share of workers crossing administrative borders is 4.47% for the NUTS 2 regions in this study, hence any potential bias arising from non-closed labor markets are negligible.

The main explanatory variable, i.e. import exposure per worker, exploits three different data sources. Trade statistics on the manufacturing subsector level are taken from World Integrated Trades Solutions (WITS) by the World Bank, which provides trade data on the level of manufacturing subsectors (NACE Rev.1) based on the UNComtrade database.[4] This feature of the WITS provides concordance of imported goods and exports to manufacturing subsectors. Employment on the manufacturing subsector level is taken from Eurostat Regional Database and the initial values of 1997 and 2002 are used to compute the regional weighting factor in equation (4.1).[5] Working-age population, which is the normalization factor in the same equation, comes from Eurostat.

Both measures of regional labor market frictions originate, as mentioned above, from individual level data in the EU LFS.[6] The survey contains information of employment status in the year the survey was conducted and the year before. Further, it asks whether the currently employed person has a permanent or a temporary contract, and in the case of the latter, also why this is the case. One possible answer is because the interviewee could not find a job with a permanent contract. These information are exploited to construct the "involuntary" inflow into temporary work out of unemployment for the first measure of labor market frictions in equation (4.3).[7] This inflow is then normalized by the total number of unemployed in the same region based on data from the same source. The second measure reverses this movement as the EU LFS also asks currently unemployed why this is the case. One of the potential answers is that a temporary contract ended. Equation (4.4) restricts this flow out of temporary employment into unemployment to those who were employed the year before the survey was conducted. Again, normalization is necessary, and for this measure the total number of employees is used.

[4] See Table 4.A1 in the appendix for an overview of manufacturing subsectors.

[5] For the UK, data in and before 1997 is not available, hence 1998 is used to compute regional specialization.

[6] Regional information is not available for Germany prior to 2002, hence the national average is used for all regions in Germany for the pre-entry period. Further, region of residence is only available on the NUTS 1 level for Germany and the United Kingdom, so all NUTS 2 regions within the same NUTS 1 region are assigned the same values for both measures of friction.

[7] France only provides the information on the "involuntary" inflow in 2006, when 65% of all inflows are involuntary. Hence, for France the indicator exploits the overall inflow into temporary contracts.

Table 4.1: Summary Statistics

	Pre-WTO entry			Post-WTO-entry		
	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.
Δ Manufacturing Employment Share	146	-0.099	1.079	146	-0.937	0.841
Δ Service Employment Share	146	2.982	1.673	146	1.319	1.522
Δ Construction Employment Share	146	0.236	1.133	146	0.269	0.676
Δ Public Service Employment Share	146	1.494	0.915	146	1.123	0.907
Δ Unemployment Rate	146	-2.821	5.043	146	0.339	4.147
Δ Labor Force Particpation Rate	146	2.433	2.816	146	1.982	2.897
Δ Manufacturing Log Hourly Wage	146	0.061	0.111	146	0.048	0.131
Δ Service Log Hourly Wage	146	0.068	0.087	146	0.025	0.084
Δ Construction Log Hourly Wage	146	0.038	0.175	146	0.006	0.141
Δ Public Service Log Hourly Wage	146	0.046	0.085	146	0.015	0.084
Δ IPW (EU)	146	0.263	0.314	146	0.960	0.601
Δ NPW (EU)	146	0.192	0.255	146	0.695	0.432
RLMF (Involuntary Emp → UE)	146	0.191	0.133	146	0.183	0.191
RLMF (Involuntary UE → Temp. Job)	146	5.595	7.187	146	5.786	8.326
Employment share Manufacturing	146	13.674	4.769	146	13.288	4.855
Employment share Services	146	27.374	7.170	146	30.609	7.257
Employment share Construction	146	5.054	1.597	146	5.279	1.304
Employment share Public Services	146	20.617	3.771	146	22.425	3.923
Unemployment Rate	146	9.857	7.898	146	7.523	8.175
Labor Force Particpation Rate	146	76.816	7.584	146	79.903	6.905
Percent tertiary education	146	18.330	6.362	146	21.194	7.139
Percent of employment among women	146	53.126	12.204	146	57.989	11.232
Share Water	146	2.194	2.449	146	2.194	2.449
Coarse Fragements	146	13.481	4.262	146	13.481	4.262

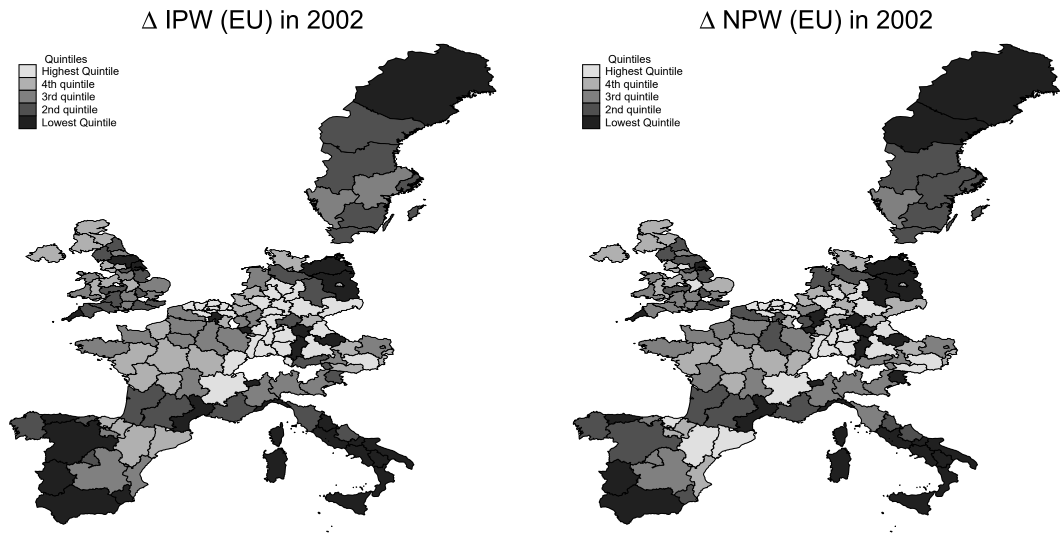
Notes: The table compares outcome and explanatory variables of the 146 NUTS II regions in the data set before and after China joined the WTO. In case of changes, the first period goes from 1997 to 2001, while the post-WTO entry period goes from 2002 to 2006. When levels are used, the summary statistics give the beginning-of-period values, i.e. 1997 and 2002 for the respective period.

The sources which were used to construct the variables of interest, i.e. labor market frictions and import exposure per worker, are the same as for the control variables. The initial share of sectoral employment shares relative to working-age population also come from the ERD and Eurostat. With the help of the EU LFS, this paper computes both the share of tertiary education and the percentage of women in employment in each region. As Chinese import competition can be amplified through housing markets (see Xu et al. (2019)), the analysis accounts for geographic housing supply conditions, by including two indicators. First, the percentage of land covered by water and wetlands provided by Eurostat, and second the percentage of coarse fragments is taken from the LUCAS Topsoil data Panagos et al. (2012). Both variables are measured in the year 2009, however due to the difficulty to change these variables in a significant manner, they are included to account for geographic constraints of the housing market.

Table 4.1 shows summary statistics subdivided into pre- and post-entry period for changes

in sectoral employment shares, (net) import exposure per worker using bilateral trade between the EU countries and China, both measures of regional labor market frictions and various control variables. The reduction in manufacturing employment is more than ninefold between 2002 and 2006 compared the previous five-year period, which suggests that Chinese imports affected manufacturing as (net) import competition is significantly higher in the post-period. On the other hand, the services sector experiences a stronger rise in the first period compared to the post-entry years. Possibly, this reflects that other factors such as technological progress influence - see e.g. argumentation in Dauth et al. (2017) - are responsible for the rise in the service sector. The construction sector experiences a slightly higher inflow relative to working-age population in the second period, while the increase in public service employment is somewhat larger in the first period. The unemployment rate drops sharply during the first period and rises slightly during the second period, generating a huge gap between the pre- and post-entry periods.
Interestingly, real log hourly wages are always increasing less during the second period, i.e. after China entered the WTO. This finding holds for all sectors, but is particularly strong in the non-manufacturing sectors. Relative to the first period, e.g. in construction the rise in real wages during the second period only equals about 18% that of the first period, and in public services this is equal to about 35%. On the other hand, the reduction in wage increase in manufacturing is equal to 20%. This is an indication that low-skilled workers are more adversely affected by the rise in Chinese import competition than high-skilled workers.

Figure 4.2: Quintile distribution of regional indicators for (net) import exposure in 2002



These maps shows the spatial variation of (net) import exposure (Δ IPW and Δ NPW) for the eight European economies in the year 2002. Each NUTS 2 region is sorted into one out of five quintiles, with darker colors indicating a higher degree of import competition from China.

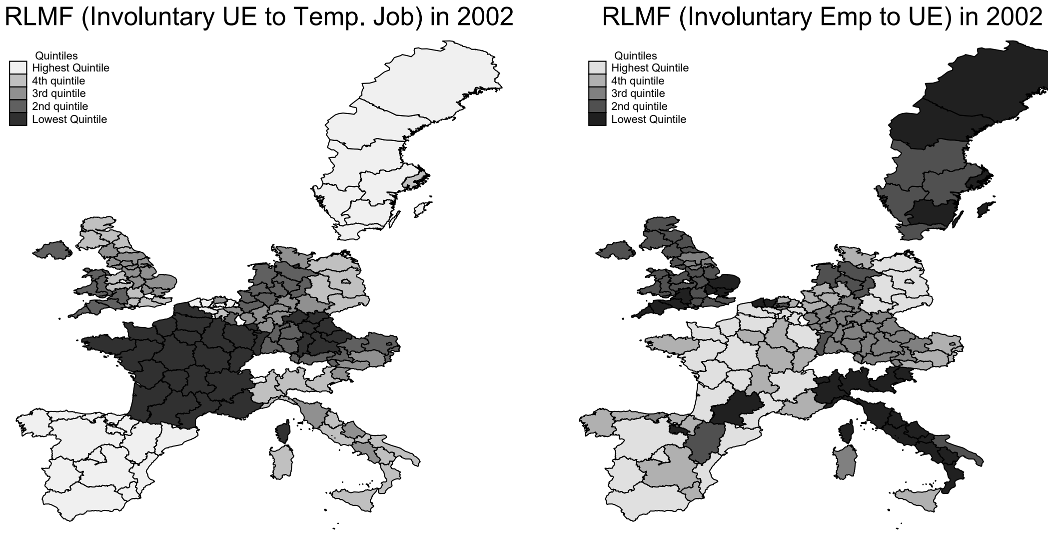
Flows from unemployment into involuntary temporary jobs are also rising, indicating a higher use of temporary contracts for workers entering employment. On the other hand, the flow from temporary contracts to unemployment falls slightly, which may be due to the fact that more often successive temporary contracts are handed out to employees. Murray (1999) highlights the high limits on the duration of successive temporary contracts. Berton et al. (2011) and Gash (2008) highlight the high chance for successive temporary contracts. Further, as a result Berton et al. (2011) find that the transition from a temporary position into a permanent contract can be long.

The services sector is by far the largest sector in the eight European economies under scrutiny as it is nearly double the size of manufacturing in 1997. Both import and (net) import exposure grow significantly over time, which reflects China's rising importance in world trade. The control variables behave over time as expected, both the share of tertiary education and of employment among women grow substantially, groups typically associated with the growth of service employment. There are no changes over time in the share of water or of coarse fragments.

Figure 4.2 shows the spatial distribution of the import and net import shock per worker in the European economies included in this study. The resemblance with the geographic dispersion with (Colantone and Stanig, 2017, Fig. 4) is striking and supports the correct measurement of the exposure to Chinese exports. As visible in the left panel of the figure, the regions most exposed to Chinese import competition are located in South and Central Germany, North East Spain and the North of Italy. The North West of England is also quite strongly exposed to Chinese goods' penetration. The right panel of the same figure shows that the geographic distribution of the net import shock is very similar to the one of import exposure. However, some German regions are less exposed when accounting for exports. This finding is not surprising given that Germany is the only European economy that could substantially increase its exports to China.

Figure 4.3 presents the spatial variation of both regional labor market frictions measures in the same year, namely 2002. The left panel shows the flow from unemployment into "involuntary" employment with a temporary contract, and the right panel shows the measure exploiting the flow from temporary employment into unemployment. France and Spain are the most rigid with both measures, and all their regions are in one of the highest two quintiles. This is not surprising giving that, as Bentolila and Dolado (1994) finds, temporary contracts spread in both countries already in the 1980s. Generally, these two countries are also considered to have more rigid labor markets within continental Europe. Italy and the United Kingdom are medium rigid with both measures, though the South of Italy is considered more rigid than the North, especially with the latter measure. The south of Italy historically suffered from higher unemployment rates - which is often interpreted as a sign of labor market frictions - compared to North Italy, hence suggesting that the regional difference in labor market frictions is reflected in this sense as well. Germany, somewhat surprisingly, is the least rigid in 2002, given that it was considered "sick man" of Europe previous to the Hartz Reforms implemented between 2003 and 2005. Probably,

Figure 4.3: Quintile distribution of regional labor market frictions measures 2002



These maps shows the spatial variation of regional labor market frictions (RLMF) for the eight European economies in the year 2002. The left panel shows the involuntary flow from unemployment (UE) into a temporary job, whereas the right panel shows the flow in the opposite direction. Each NUTS 2 region is sorted into one out of five quintiles, with darker colors indicating a higher degree of import competition from China.

these measures are low because fixed-term contracts were not strongly used in Germany before the labor market reforms, hence in- and outflow out of these contracts was low compared to other countries. The main argument behind the lower values for Germany compared to the United Kingdom seem to be that the reason for not having a permanent job is that many temporary jobs are covering training periods in Germany, not because a permanent job could not be found. For the second measure, the reason for being unemployed during the interview is relatively more common in the United Kingdom than in Germany, where the main reason is, by far, dismissal. Coinciding with previous research, however, is the regional distribution of labor market frictions within Germany. Burda (2006) finds that labor markets in East Germany do not adjust because they are more rigid than in West Germany, which is reflected in both measures of labor market friction.

4.3 Analysis

This section presents three different identification approaches using instrumental variable estimation for import exposure to Chinese imports, and acknowledge that its interactions with labor market frictions are endogenous as well. The three different estimation strategies differ in their way how to treat the interaction term. The first part explains how these treatments differ. Subsequently, the paper reviews the results for all major sectors of employment and the non-employment rates applying all three different identification strategies. The sectoral differentiation helps in understanding the shifting mechanisms induced by trade and whether labor market frictions exacerbate or mitigate these market forces. It discusses the conditional impact of regional trade exposure on manufacturing employment shares in NUTS II regions first, as China's supply-driven exports occur in this sector. It then investigates other sectors of employment, namely (private) services, construction and non-market services. Finally, the paper studies the two non-employment options, namely unemployment and labor force participation. The results indicate that public service employment absorbs most of the adverse shock on manufacturing, while construction and the unemployment rate are unresponsive. The services sector tends to absorb the trade shock as well, while the labor force participation rate is falling. However, the estimates are estimated with noise.

4.3.1 Identification strategy

The instrument for the main effect, i.e. import competition per worker, was developed by Autor et al. (2013). The authors exploit exports from China to other advanced economies to explain US imports of Chinese imports in order to identify the supply-driven component of Chinese goods' penetration to the US. As this study focuses on a panel of countries in Europe, European imports from China are explained using Chinese exports to the US (and other high-income countries), similar to Colantone and Stanig (2017). Thus, this paper's identification strategy also constitutes a two-stage least squares (2SLS) similar to most previous studies.

The main research question of this paper is to causally identify whether labor market frictions conditions the response of labor market outcomes, especially with respect of sectoral employment shares and wages. In order to determine whether labor market responses are idiosyncratic subject to different degrees of the use of temporary contracts in the regional labor market, the estimation equation includes an interaction term between the endogenous import competition per worker and labor market friction:

$$\Delta Y_{rt}^{k} = \gamma_t + \gamma_c + \beta_1 \Delta IPW_{rt}^{EU} + \beta_2 RLMF_{rt} + \beta_3(\Delta IPW_{rt}^{EU} \times RLMF_{rt}) + \boldsymbol{X'}_{rt}\Theta + \varepsilon_{rt}, \quad (4.5)$$

where ΔY_{rt}^{k} is the quinquennial change of either employment shares or log hourly wages of the respective sector k in region r. The regional change in sectoral employment shares or log wages are explained by regional differences in both import exposure per worker (ΔIPW_{rt}^{EU}) and labor market frictions ($RLMF_{rt}^{i}$), their interaction, a set of controls and a period fixed effect. In case of differences, five-year changes are used in the estimation, while level variables, such as the measurement of regional labor market frictions and the control variables, constitute beginning-of-period values. As argued in section 2.2, the identification treats the modifying variable, i.e. regional labor market frictions, as exogenous. To avoid any potential reverse causality caused by labor market developments due to trade between China and European countries, the estimation strategy exploits initial values for labor market friction. Beginning-of-period values help to circumvent this potential bias as labor market institutions are typically sluggish to adjust to market forces such as trade.

The parameters of interest are β_1 for comparison with previous studies, β_2 to determine the impact of the use of temporary contracts and β_3 for the interplay of globalization and labor market institutions, i.e. whether $RLMF^i_{rt}$ as the modifying variable reshapes the impact of import exposure per worker on employment shares and wages. The expected sign for β_1 for manufacturing employment shares is negative, as other studies like in Autor et al. (2013), Balsvik et al. (2015) and Donoso et al. (2015). For the other sectoral employment shares, the sign is expected to be positive except for the workers entered unemployment. However, as Curuk and Vannoorenberghe (2017) highlight occupational proximity, the point estimate is expected to be larger for construction than services. The coefficient β_2 for labor market frictions is assumed to be positive for sectors, where permanent employment is relatively more dominant compared to finite horizon contracts, which - based on EU LFS data - are manufacturing, services and construction (in this order). The point estimate of the interaction term, i.e. β_3 is possibly negative for manufacturing, conditional on a high use of temporary contracts, the import shock allows firms to adjust stronger in terms of employment. On the other hand, point estimates for the other sectors are likely to be positive as the higher outflow of the manufacturing sector may result in a stronger inflow of workers into unaffected sectors.

The vector of control variables $\boldsymbol{X'}_{rt}$ encompasses start-of-period employment share or log hourly wage of the respective sector k in order to account for regional convergence. To account for further regional demographic characteristics, the vector of controls includes both the share of the population with tertiary education and percentage of women in employment. Finally, Xu et al. (2019) show that the China shock operated partially through housing markets and show that the impact is reduced by 20-30% accounting for the amplification impact. Due to data constraints on regional house price developments in European regions, the vector of controls accounts for geographic housing supply restrictions based on Saiz (2010). He identifies the steepness of terrain and water as major constraints. Therefore, the vector of controls also includes the share of coarse fragments as a proxy for the former and measures the latter exactly. The estimation equation contains a period-fixed effect (γ_t) for the period prior and after China's inclusion in the WTO, i.e. before and after 2002, and a country-fixed effect (γ_t). Hence, identification relies on within-period and within-country variation. Observations are weighted by their relative size of the working-age population, and standard errors are clustered on the regional level.

The first out of three treatment methods of the endogenous interaction term ($\Delta IPW^{EU}_{rt} \times RLMF_{rt}$) follows the argumentation of Nizalova and Murtazashvili (2016) and Bun and Harrison (2018). Both argue that, if the impact of the main endogenous regressor is controlled for, then the interaction term can be treated as exogenous and its OLS estimator is unbiased and consistent. In other words, if the estimation strategy applies the 2SLS approach for the constitutive term of the endogenous regressor, its interaction with the modifying variable can be interpreted as any other OLS coefficient. Subsequently, this paper refers to this treatment of the interaction term as the "OLS" estimates. Hence, the first stage for the OLS estimation strategy takes on the following form:

$$\Delta IPW_{rt}^{EU} = \gamma_t + \gamma_c + \alpha_1 \Delta IPW_{rt}^{US} + \alpha_2 RLMF_{rt} + \alpha_3 (\Delta IPW_{rt}^{EU} \times RLMF_{rt}) + \boldsymbol{X'}_{rt}\Gamma + \zeta_{rt}, \tag{4.6}$$

which is analogous to Autor et al. (2013) with the modification of Colantone and Stanig (2017) to use US imports of Chinese goods to explain regional import competition for European labor markets. As standard, with the 2SLS, the other control variables, in this case the vector of controls, regional labor market frictions and its interaction with EU import competition. The OLS approach does not use US import exposure in the interaction term as this variable can be interpreted as standard OLS coefficient in equation (4.5).
The second approach follows another approach by Bun and Harrison (2018) to treating the endogenous interaction term, who were inspired by Kelejian (1971) to exploit a vector of second-order polynomials as instruments. The authors argue that the previous literature focused on IV estimation of linear models, and hence this approach did not receive much attention. This treatment of the endogenous interaction term implies two first-step regression equations before estimating equation (4.5):

$$\Delta IPW_{rt}^{EU} = \gamma_t + \gamma_c + \pi_1 \Delta IPW_{rt}^{US} + \pi_2 RLMF_{rt} + \boldsymbol{X'}_{rt}\Phi + \boldsymbol{Z'}_{rt}\Psi + \kappa_{rt}, \text{and} \tag{4.7a}$$

$$\Delta IPW_{rt}^{EU} \times RLMF_{rt} = \gamma_t + \gamma_c + \delta_1 \Delta IPW_{rt}^{US} + \delta_2 RLMF_{rt} + \boldsymbol{X'}_{rt}\Omega + \boldsymbol{Z'}_{rt}\Lambda + \xi_{rt}, \text{where} \tag{4.7b}$$

$$\boldsymbol{Z}_{rt} = [RLMF_{rt}^2 \qquad \boldsymbol{X'}^2_{rt} \qquad RLMF_{rt} \times \boldsymbol{X'}_{rt}]'. \tag{4.7c}$$

This approach does not require any external instruments for the interaction term, but relies only on internal instruments. These are the square product of the modifying variable, the squares of the control variables in the vector $\boldsymbol{X'}_{rt}$ and their cross-products.[8] In the following, this paper refers to this estimation approach as the "functional form" because this instrument relies on polynomial approximation of the interaction term, i.e. it exploits on the functional form of the interaction term.
The third approach follows an empirical application of Aghion et al. (2005), who instrument for the endogenous constitutive term and the interaction term using the instrumental variable itself and the interaction of the instrument with the conditioning variable, here re-

[8] Bun and Harrison (2018) also include the product of the squared modifying variable with the control variables, and the product of the square of all exogenous variables with the conditioning variable, but are left out here.

gional labor market frictions (*RLMF*). This strategy, which will subsequently be referred to as "IV" approach, also assumes that the interaction term is endogenous and requires it to be instrumented, hence, like the "functional form", resulting in two first-stage regressions:

$$\Delta IPW_{rt}^{EU} = \gamma_t + \gamma_c + \lambda_1 \Delta IPW_{rt}^{US} + \lambda_2 RLMF_{rt} + \lambda_3(\Delta IPW_{rt}^{US} \times RLMF_{rt}) + \boldsymbol{X'}_{rt}\Pi + \omega_{rt}, \text{and} \tag{4.8a}$$

$$\Delta IPW_{rt}^{EU} \times RLMF_{rt} = \gamma_t + \gamma_c + \tau_1 \Delta IPW_{rt}^{US} + \tau_2 RLMF_{rt} + \tau_3(\Delta IPW_{rt}^{US} \times RLMF_{rt}) + \boldsymbol{X'}_{rt}\Upsilon + \rho_{rt}. \tag{4.8b}$$

The correct interpretation of the interaction term is a crucial element of this paper, especially for policy recommendations based on the results shown in the next section. In order to also gain graphical evidence on whether and how the impact of regional import exposure from China on labor market outcomes in different sectors varies over the whole distribution, this paper presents marginal effects plots based on Brambor et al. (2005). In general, these plots are helpful because the point estimates may not be of particular interest, instead the marginal effect of import exposure in equation (4.5), i.e. $(\beta_1 + \beta_3 \times RLMF_{rt})$, is of interest. Marginal effect plots indicate how this marginal effect changes over the distribution of the modifying variable, including the correct standard errors for each point in the distribution of the modifying variable.

4.3.2 Employment

The empirical specifications outlined at the beginning of the section allow this paper to determine the causal relationship between sectoral employment shares and both import shocks and labor market frictions on a regional level for eight European economies. The empirical findings help to answer the research questions laid out in the beginning: First, whether and by how much manufacturing employment shares contract subject to higher import competition as previous studies have shown. Second, if stronger local labor market frictions mitigate or amplifies the adverse shock to the manufacturing, represented by the point estimates of the interaction terms. To answer the third question, namely whether, and if yes, which sector absorbs the negative impact on the manufacturing sector, the paper conducts the same analysis for services, construction, private services, the unemployment rate and labor force participation rate.

The remainder of this section presents the regression results for employment shares and (log) hourly wages by sector with both indicators of regional labor market frictions and the three different identification strategies, resulting in six estimation results for each sector.

Marginal effects plots based on Brambor et al. (2005) complement the analysis because only the point estimates do not provide enough information about the whole distribution of the modifying variable if it is non-binary. Further, robustness checks exploiting net imports and imports to other advanced economies validate the baseline results.

4.3.2.1 The decline of the manufacturing sector

Hanson and Robertson (2008) show that between 2000 and 2005 the share of manufacturing accounted for 89% of China's merchandise exports. Given it's sharply rising exports to advanced economies, the increasing import competition most likely affects the manufacturing sector directly. Table 4.2 illustrates that the import shock reduces manufacturing employment in an economically and statistically significant way, the point estimates for the second stage are shown in panel I. Column (1) indicates that an increase of $1,000, with 2005 as the base year, in import exposure per worker over a five-year period reduces the manufacturing employment share relative to the working-age population by 1.29 percentage points. However as Brambor et al. (2005) highlight, this coefficient is only true if the modifying variable takes on the value zero. As both conditioning variables have been standardized, this means that the reduction of the manufacturing employment share by 1.29 percentage points occurs in regional labor markets with average labor market frictions.

The average of all six point estimates is minus 1.04 percentage points. The sign is in line with previous research and the subsequent assumption about the sign of β_1 in equation (4.5). The size of the same parameter exceeds the point estimate of around .6 by Autor et al. (2013, Table 3) for the United States. However, this is not surprising given the sample of countries included in the study. Donoso et al. (2015) find significantly larger impact on Spanish regional labor markets, with point estimates around two for Spain, and Balsvik et al. (2015) find a point estimate of .78 for Norway. Further, though the results are not directly comparable because these studies use growth rates instead of differences, both Malgouyres (2017) for France and Federico (2014) for Italy find strong reductions in manufacturing employment growth due to rising import competition from low-wage countries.

Balsvik et al. (2015) and Donoso et al. (2015) argue that key differences in the magnitudes may be due to labor market institutions. Especially the latter argue that adjustment in quantities is stronger in Spanish regions because in a rigid labor market adjustments of demand shock are mainly remarkable in quantities, i.e. employment. The point estimates of the interaction support this view as all six of them are negative and with one exception is statistically significant at the 5% level - again in line with our expectations about β_3 in equation (4.5). The negative coefficients imply that, conditional on a higher labor market frictions, the contraction in manufacturing employment share due to higher

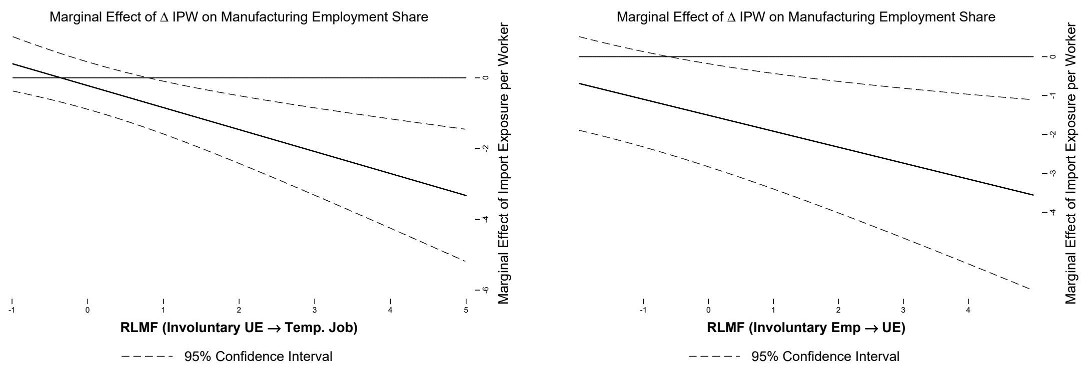
Table 4.2: Conditional effect of import exposure on manufacturing employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-1.26**	-0.33	-1.52***	-1.35***	-1.51**	-0.22
	(-1.98)	(-1.24)	(-4.28)	(-4.06)	(-2.23)	(-0.64)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.23		-0.34		-0.41**	
	(-1.59)		(-1.60)		(-2.55)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.52***		-0.15		-0.62***
		(-2.86)		(-0.59)		(-3.43)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.01***	0.02***	0.01***	0.01***	0.01***	0.01***
	(3.70)	(5.28)	(3.51)	(3.70)	(4.00)	(4.35)
R^2	0.67	0.74	0.74	0.74	0.67	0.68
F-Statistic	13.69	27.88	12.35	13.68	15.99	18.95
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.10)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.11)
R^2			0.75	0.41	0.80	0.91
F-Statistic			3.56	2.20	50.41	171.89

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in manufacturing employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

import exposure is stronger. As Spain and France have more rigid labor markets, these are the countries which are hit the strongest by supply-driven imports from China. On the other hand, less rigid labor markets like Germany and the United Kingdom did not experience a statistically significant reduction in manufacturing employment shares as the marginal effects plots in Figure 4.4 show. In the figure, both panels show that with lower labor market frictions the impact on manufacturing employment is less pronounced and possibly even insignificant.

Figure 4.4: Marginal Effects of Import Exposure per Worker on Manufacturing Employment conditional on Regional Labor Market Frictions



The marginal effects plots show the response of manufacturing employment per working age population to Chinese import competition. The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE $\rightarrow$ Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp $\rightarrow$ UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of Table 4.2.

Panels II and III in table 4.2 shows the point estimates of the first-stage regressions. As outlined above, all three different identification strategies only differentiate in their treatment of the interaction term. Thus, all three approaches take into account that the main effect, i.e. import competition endogenous to (industry) demand for Chinese goods, is endogenous. Hence, following Autor et al. (2013) the imports of European countries from China is instrumented using US imports of Chinese goods. Panel II shows the point estimates of import exposure using US for explaining import competition with European imports. The range of the point estimates is between 0.01 and 0.02, and all of them are statistically significant at the 1% level and the F-Statistic is above 10 in all six specifications. The coefficients are significantly smaller than in Autor et al. (2013) for the United States, but are about half as large as those in previous studies focusing on Europe, may it be cross-country studies like Colantone and Stanig (2017) or single-country studies as Donoso et al. (2015). The lower estimates in the first stage are linked to the fact that the paper exploits imports to a large economy, i.e. the United States, as an instrumental variable for imports to smaller countries, especially Belgium, the Netherlands and Sweden.
The different treatments of the endogenous interaction term is visible in panel III of Table 4.2. The first two columns, which represent the "OLS" approach, show the results as-

suming that the interaction term can be treated as exogenous because the main effect has been taken account for. Hence, only one first stage exists for this identification strategy and panel III is empty. Columns (3) and (4) reflect the "functional" estimation method, which acknowledges that the interaction term is endogenous. Bun and Harrison (2018) propose a vector of second-order polynomials as instruments for the interaction term as it constitutes a non-linearity in itself. Because this vector is quite extensive and does not contain any economically meaningful information for the first stage, panel III only reports the R^2 and the F-Statistic, which are below 10 in both cases. This is largely due to the introduction of country-fixed effects, which limit the variation, and the large second-order polynomial of control variables used as instruments. However, as the interaction term itself, or rather its functional form, gives rise to this estimation approach, the typical value of 10 does not hold. Finally, the only specification where the interaction term is insignificant on conventional levels is Column (4), specifically where the R^2 is by far the lowest.
The last two columns show the results for the preferred specification, i.e. the "IV" approach, which instruments for the interaction term using the product of the instrument of the main effect and the conditioning variable. In this case, these are US imports from China and the measure for regional labor market frictions. The IV approach of the interaction terms constitutes the preferred specification, hence Figure 4.4 shows the results based on this estimation method. The point estimates are statistically significant at the 1% level and are about double the magnitude compared to the point estimates for the first stage of the main effect in Panel II. The F-Statistics exceed 50 and 174, respectively.

4.3.2.2 Noisy response of the services sector

The natural question following from the result of an adverse impact on manufacturing employment is what happens to displaced workers. They can potentially enter either employment in other sectors, become unemployed or leave the labor force altogether. Theoretically, Caliendo et al. (2019) argue that other sectors such as services and construction profit from the trade shock due to cheaper intermediate inputs from China, which should lead to a rise in employment in these sectors. However, the empirical evidence is mixed. Autor et al. (2013) find no change in non-manufacturing employment, instead unemployment rises due to higher import competition from China. Balsvik et al. (2015) find that employment in "other" sectors rises slightly, but find that the largest increase occurs in unemployment. Donoso et al. (2015) find an increase in employment related to construction and services related to it. For Denmark, Keller and Utar (2016) find that mid-skilled workers in manufacturing reallocate to either high-skilled or low-skilled service jobs after a trade shock, contributing to the polarization of labor markets.
Keeping in mind the timing of the rise of the service sector documented in the descriptive statistics in Table 4.1, it seems improbable that the service sector absorbs displaced

Table 4.3: Conditional effect of import exposure on services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.04	-0.17	1.21**	0.40	0.22	-0.31
	(0.07)	(-0.37)	(2.38)	(0.92)	(0.46)	(-0.53)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.05		1.24**		0.26	
	(0.41)		(2.43)		(1.27)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.25		-0.13		0.46**
		(0.90)		(-0.20)		(2.00)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.03***	0.02***	0.02***	0.02***	0.02***
	(4.96)	(5.97)	(4.32)	(4.57)	(5.18)	(5.30)
R^2	0.64	0.71	0.71	0.71	0.64	0.64
F-Statistic	24.65	35.61	18.70	20.93	26.81	28.08
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.35)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.31)
R^2			0.75	0.74	0.80	0.91
F-Statistic			2.60	2.88	53.95	177.08

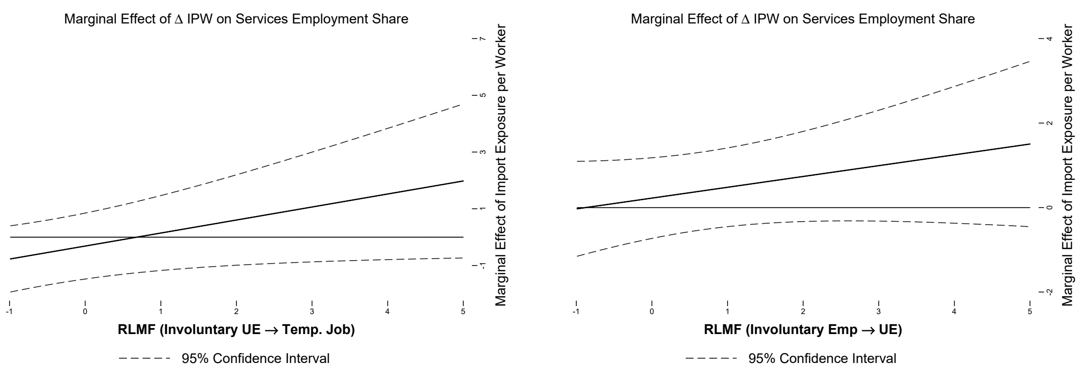
Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

workers from manufacturing after the rise in Chinese import competition. Instead, Autor and Dorn (2013) highlight the ongoing polarization of labor markets in the US, especially in the service sector, but they argue that both consumer preferences favoring variety and cheaper automation technology are the main drivers. These determinants hold particularly for low-skilled jobs, while Buera and Kaboski (2012) emphasize the role of education and the returns to skill for high-paid jobs in services, which were crucial to the rise of this sector. Further, as mentioned previously, the rise in female labor market participation lead to an increase in the share of service employment in advanced economies.

Table 4.3 displays the estimation results for the services sector, i.e. how employment in services relative to the working-age population responds to the import shock conditional on local labor market frictions. The point estimates change signs and mostly vary around zero ranging from -.24 to .33 in five out of six specifications. These five point estimates are statistically insignificant on conventional levels. Only in Column (3) the point estimate is positive, large and statistically significant at 5%. Unsurprisingly, the values of F-Statistics and point estimates of the instrument for the main effect are similar or even slightly higher in Table 4.3 compared to 4.2 for manufacturing.

All point estimates of the interaction terms are positive, but only two of them are statistically significant. The marginal effects plots in Figure 4.5 show the importance of meaningful standard errors if the modifying variable is non-binary. Even though the interaction term in Column (6) is statistically significant at 5%, this does not translate into a statistically significant effect across the whole distribution of the measure of regional labor market frictions. The lack of a response in services to trade shocks (at least with low-wage countries) supports the notion that other drivers, such as rising skills and decreasing automation costs, are important determinants of the rise of the service sector.

Figure 4.5: Marginal Effects of Import Exposure per Worker on Services Employment conditional on Regional Labor Market Friction



The marginal effects plots show the response of service employment per working age population to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.3.

4.3.2.3 No absorption by the construction sector

The subsequent option for the absorption of the trade shock is the construction sector. Caliendo et al. (2019) argue that the service sector is more important than the construction sector for the absorption of the trade shock in the United States. The importance of the construction sector is shown by Charles et al. (2016) and Donoso et al. (2015), The former argue that the rise in construction masked the decline of manufacturing employment in the United States, especially for low-skilled workers, while the latter shows that construction experience a large expansion during the decline of manufacturing in Spain. Further, Curuk and Vannoorenberghe (2017) point out that occupational similarity and regional proximity matter for labor reallocation. Regional proximity is typically given for both the services and the construction sector as they constitute non-tradable sectors and hence locate close to their customers due to high transportation costs. However, using job flows in Sweden Neffke and Henning (2013, Fig. 1) show that occupational similarity between manufacturing and construction is higher than between the former and services. The findings in this study do not corroborate the findings of Charles et al. (2016) and Donoso et al. (2015) on a European level. Again remembering the summary statistics in Table 4.1, this does not come surprising as there was no substantial difference in the increase of the construction sector before and after China entered the WTO in 2001. Table 4.4 shows the results for the construction sector using the three different treatments of the interaction terms and the two measures of regional labor market frictions. The point estimates of the main effect, i.e. import competition from China, are largely negative and range between -.27 and .09. Only the former is statistically significant at the 10% level, the other five parameters are statistically insignificant. Analogous to the results of the first stages for manufacturing and the services sector, the point estimates for the instrumental variable shown in Panel II are about .02, and the F-Statistics always exceed 10.
The interaction terms are also largely negative, and in three out of these five specifications statistically significant on conventional levels. The only specification, where it is positive, is Column (3), i.e. the functional approach using the involuntary inflow from employment to unemployment as the measure for regional labor market frictions. Coincidentally, this is the same specification, for which the point estimate of the main effect is positive. The estimation results provide evidence that the construction sector does not absorb the adverse impact of the trade shock on the manufacturing sector, independent of the level of regional labor market frictions. Figure 4.6 show this very clearly. The right panel does not show any significant impact on construction employment across the whole distribution, the left panel even predicts a negative impact of the trade shock on construction employment.

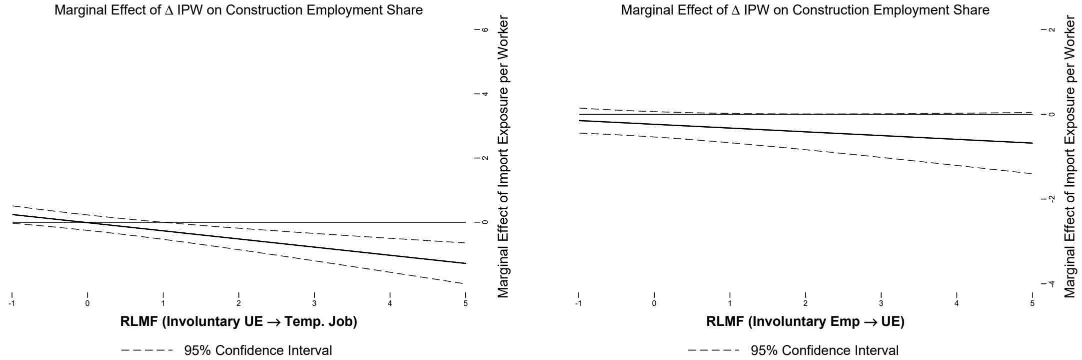
These findings about the construction sector can still be in line with the argument by Xu et al. (2019) that the import shock operates partly through the housing market and

Table 4.4: Conditional effect of import exposure on construction employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.18	-0.09	-0.15	-0.10	-0.23	-0.01
	(-1.20)	(-0.82)	(-0.84)	(-0.75)	(-1.54)	(-0.12)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.03		0.06		-0.09	
	(-0.54)		(0.48)		(-1.46)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.15**		-0.29**		-0.25***
		(-2.45)		(-1.96)		(-4.17)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(5.18)	(6.02)	(5.32)	(5.69)	(5.23)	(5.54)
R^2	0.66	0.72	0.70	0.71	0.66	0.66
F-Statistic	26.86	36.30	28.32	32.34	27.39	30.69
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.30)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.76)
R^2			0.75	0.77	0.80	0.92
F-Statistic			3.65	1.59	53.31	189.44

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in construction employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Figure 4.6: Marginal Effects of Import Exposure per Worker on Construction Employment conditional on Regional Labor Market Friction



The marginal effects plots show the response of construction employment per working age population to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.4.

the findings by Donoso et al. (2015) and Charles et al. (2016). Either, the rise in import competition from China is not directly related to the house price developments and the demand for construction employment, or the import shock occurred simultaneously to a financial shock in the form of credit supply or speculative bubbles.

4.3.2.4 Shock Absorption by Public Service Sector

This non-significant results might be explained by the focus on private services employment. For the United States, Caliendo et al. (2019) show that, apart from "Other Services", education and health are contributing most to employment gains in non-manufacturing, which are typically considered as non-market services in most European countries. Therefore, this section investigates whether a similar response takes place in the economies subject to investigation, i.e. whether public services absorb the adverse impact of the import shock on the manufacturing sector.

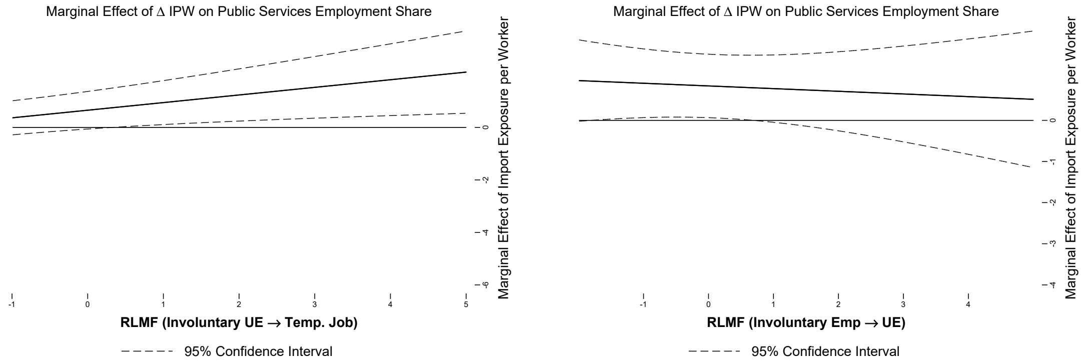
Table 4.5 presents the estimation results in the same fashion as above for manufacturing, (private) services and construction. All of the six specifications exhibit positive coefficient estimates of the main effect, i.e. given average regional labor market frictions, and four of them are statistically significant at least at the 10% significance level. These findings support the notion that public service employment tends to absorb the adverse impact of the trade shock on the manufacturing sector. Non-market services encompass education and health, and thus the findings here for eight European countries support the notion by Caliendo et al. (2019) that these sectors absorb the trade shock. Both panels in Figure 4.7 support this notion across most of the distribution of regional labor market frictions with meaningful standard errors included.

Table 4.5: Conditional effect of import exposure on public services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.84*	0.48	0.52**	0.37	0.84**	0.66*
	(1.89)	(1.56)	(2.02)	(1.37)	(2.13)	(1.80)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.06		0.17		-0.07	
	(-0.51)		(0.93)		(-0.43)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.52***		1.13***		0.29**
		(3.21)		(4.24)		(2.54)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(4.80)	(5.80)	(4.37)	(4.71)	(5.00)	(5.10)
R^2	0.64	0.71	0.70	0.70	0.64	0.64
F-Statistic	23.01	33.69	19.08	22.23	25.01	25.99
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.13)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.31)
R^2			0.75	0.44	0.80	0.91
F-Statistic			4.21	2.11	50.84	177.26

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in public services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Figure 4.7: Marginal Effects of Import Exposure per Worker on Public Services Employment conditional on Regional Labor Market Friction



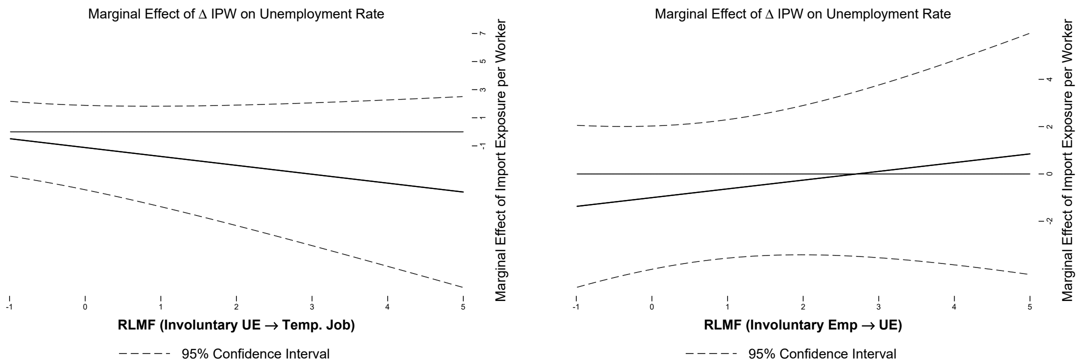
The marginal effects plots show the response of construction employment per working age population to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.4.

4.3.2.5 Non-employment alternatives

As argued above, displaced manufacturing workers have three broad options after losing employment induced by rising import competition. Besides working in another sector, two non-employment responses are possible. First, they can be unemployed and seek re-entering the labor force. Dauth et al. (2017) show that the rise in service employment in Germany comes from re-entrants, i.e. former employees in the manufacturing sector first entered unemployment and then re-entered the service sector. The second alternative is exiting the labor force, which is more likely to be an option for older workers who are close to retirement and simply advance it. Autor et al. (2013) find that the trade shock affects both non-employment options, namely that the unemployment rate is rising and that labor force participation is falling. Neither any of the two single-country studies, i.e. Balsvik et al. (2015) for Norway and Donoso et al. (2015) for Spain, fully confirm the results. The former finds an increase in unemployment, especially for low-skilled workers, and no significant change in labor force participation. The latter even finds a negative impact of the trade shock on the unemployment rate, though estimated with noise, and also no effect on the labor force participation rate.
Tables 4.6 and 4.7 show the estimation results for the unemployment rate and the labor force participation rate, respectively. The results support the findings by Donoso et al. (2015), i.e. the point estimates are all negative and, with one exception in Column (3), all statistically insignificant. This non-response is independent of the level of labor market frictions as indicated by the interaction terms, i.e. the unemployment rate never reacts in a statistically significant way. The sign of the point estimates of the interaction terms differs, two are positive and four are negative. However, the interaction terms are, again with

one exception in Column (4), estimated with noise. Figure 4.8 depicts the marginal effects plots using the preferred estimation method, i.e. the “IV” approach of the interaction term. In both cases, the meaningful standard errors are so large that the unemployment rate is never statistically significant across the whole distributions of either measure of regional labor market frictions, even though the estimated signs of the interactions terms differ.

Figure 4.8: Marginal Effects of Import Exposure per Worker on Public Services Employment conditional on Regional Labor Market Friction



The marginal effects plots show the response of the unemployment rate to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.6.

The second non-employment alternative is dropping out of the labor force. For the two single-country studies in Europe there was no significant effect on the labor force participation rate. The estimation results in Table 4.7 support these findings. The point estimates of the main effect, conditional on average regional labor market frictions, are ranging between -.91 and .09, and are always estimated with noise. This is in line with expectations and that some displaced workers are advancing retirement. The non-employment alternative of dropping out of the labor force is more likely for older workers, which is why the estimated effected may be insignificant due to the lack of age information in the data. As with all other specifications, the coefficients of US imports from China in the first stage are around .02, statistically significant and the F-Statistics exceed 10.

The interaction terms using either measure of regional labor market frictions are negative in five cases, indicating that a higher difficulty to re-enter employment (under a permanent contract) provides more reason to drop out of the labor force, and in the case of older displaced workers to advance retirement. However, only one of the five coefficients of the interaction term with a negative sign is statistically significant, the remaining ones are estimated with noise similar to the one with a positive sign. However, the left panel of Figure 4.9 shows the marginal effects plot where the interaction term is negative and statistically significant at the 5% level, i.e. Column (6) of Table 4.7. Yet, the meaningful

Table 4.6: Conditional effect of import exposure on the unemployment rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.74	-1.12	-3.91*	-3.51	-1.00	-1.12
	(-0.45)	(-0.85)	(-1.93)	(-1.59)	(-0.65)	(-0.73)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.65		-0.39		0.37	
	(1.21)		(-0.41)		(0.73)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.64		2.66*		-0.63
		(-0.94)		(1.68)		(-1.30)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(4.94)	(5.96)	(4.59)	(4.63)	(5.11)	(5.27)
R^2	0.64	0.72	0.70	0.70	0.64	0.65
F-Statistic	24.44	35.47	21.06	21.46	26.15	27.72
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.13)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.22)
R^2			0.76	0.73	0.80	0.91
F-Statistic			3.44	2.54	50.84	174.66

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in the unemployment rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

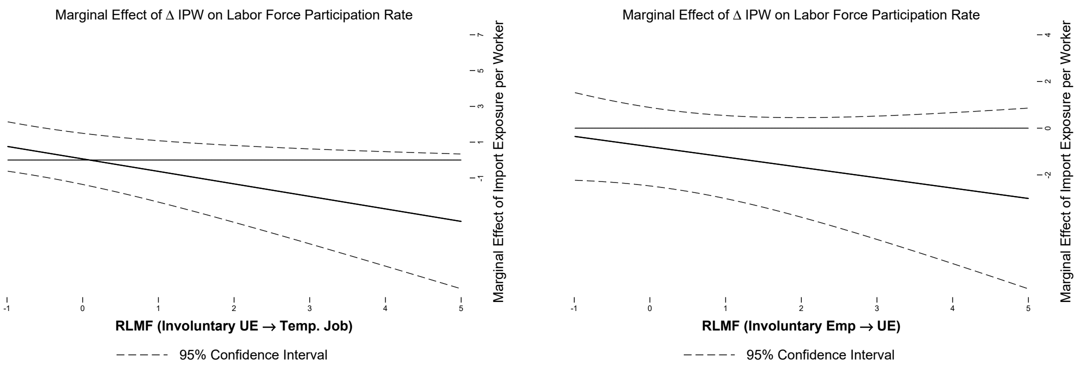
Table 4.7: Conditional effect of import exposure on the labor force participation rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.79	-0.05	-0.93	-0.72	-0.79	0.07
	(-0.83)	(-0.08)	(-1.31)	(-1.18)	(-0.92)	(0.09)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.44		-0.52		-0.44	
	(-1.36)		(-0.90)		(-1.20)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.53		0.13		-0.70**
		(-1.27)		(0.15)		(-2.22)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(5.03)	(6.00)	(5.50)	(5.68)	(5.24)	(5.34)
R^2	0.64	0.71	0.69	0.70	0.64	0.64
F-Statistic	25.29	35.99	30.21	32.21	27.45	28.55
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04***	
					(7.17)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05***
						(13.29)
R^2			0.76	0.73	0.80	0.91
F-Statistic			4.00	2.02	51.41	176.51

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in the labor force participation rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

standard errors indicate that the labor force participation rate never show a significant response across the whole distribution of regional labor market frictions. This conclusion also holds for the second measure of regional labor market frictions in the right panel.

Figure 4.9: Marginal Effects of Import Exposure per Worker on Public Services Employment conditional on Regional Labor Market Friction



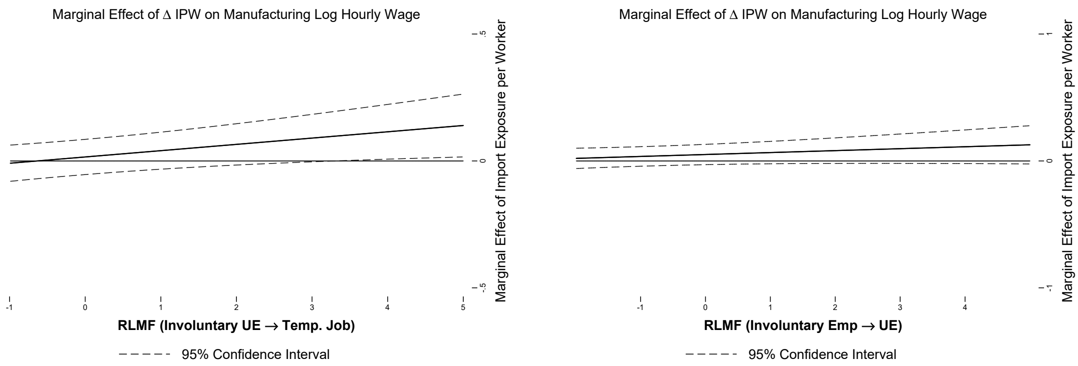
The marginal effects plots show the response of the unemployment rate to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.7.

4.3.3 Wages

Besides employment shares per working-age population, wages are another area how employers can adjust to an adverse trade shock. Due to probable changing workforce compositions in all sectors, the results of this section need to be interpreted cautiously. For the United States, Autor et al. (2013) find an adverse impact of Chinese import competition on manufacturing wages despite an upward bias on wages as low-skill manufacturing workers are more prone to lose employment. Using the same empirical estimation strategy as for the employment response, now this study exploits the quinquennial changes in log hourly wage of the same sectors as dependent variables. Given that this paper cannot determine which groups of workers are more hit by the rising Chinese exports, the bias can go in both directions. However, the standard results from empirical studies is that demand for low-skilled workers falls with rising imports from low-income countries. Hence, an upward bias is also likely to be prevalent in these estimation results.

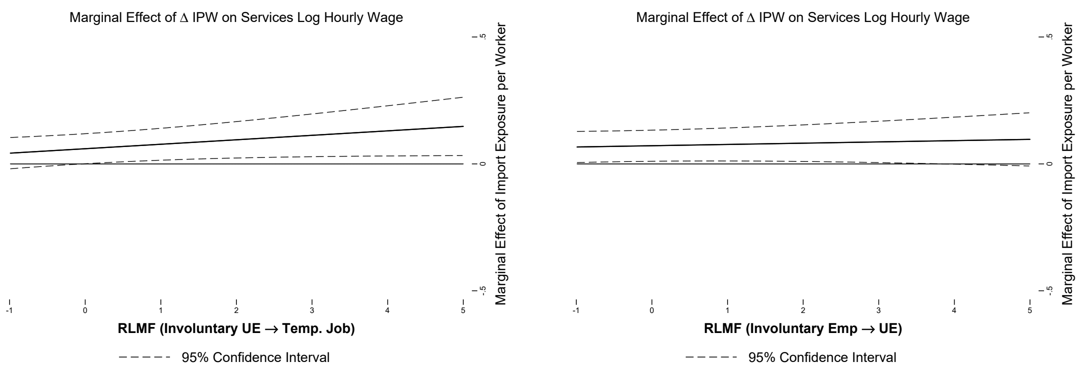
Analogous for the employment response, Figures 4.10 to 4.13 show the marginal effects plots based on the IV estimates for the three sectors manufacturing, (non-public) services, construction and non-market services. The results with the other two estimation approaches, i.e. the OLS and the functional approach, yield very similar outcomes and are shown in Tables 4.B1 to 4.B4 in the appendix. Figure 4.10 shows a slight upward trend in log hourly wages if labor market frictions are higher, i.e. also when the loss in manufacturing employment is larger. This would be in line with previous findings, that the adverse trade shock affects low-skilled workers stronger. However, there is no statistically significant impact on manufacturing wages across the whole distribution of regional labor market frictions. Log hourly wages in the services and in the construction sector also seem to rise with labor market frictions, but are hardly statistically significant at the 5% significance level.

Figure 4.10: Marginal Effects of Import Exposure per Worker on Manufacturing Wages conditional on Regional Labor Market Frictions



The marginal effects plots show the response of manufacturing hourly wages to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.B1.

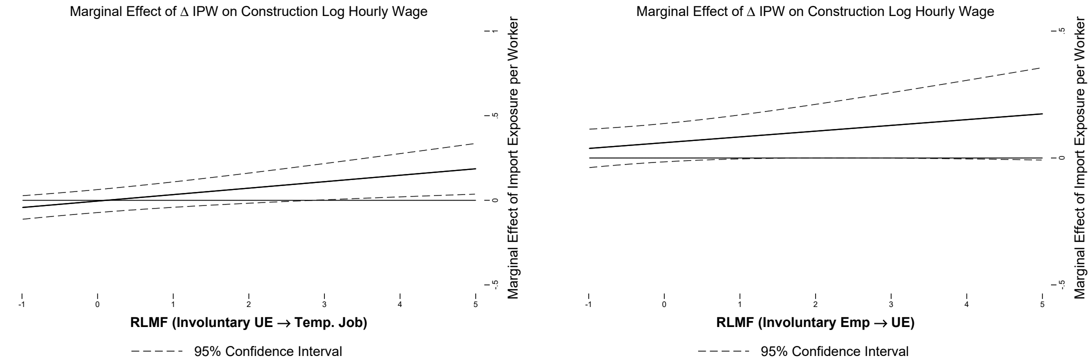
Figure 4.11: Marginal Effects of Import Exposure per Worker on Services Wages conditional on Regional Labor Market Frictions



The marginal effects plots show the response of service hourly wages to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.B2.

Figure 4.13 illustrates the wage response of non-market services to the import shock conditional on the level of regional labor market frictions. Despite the absorption of

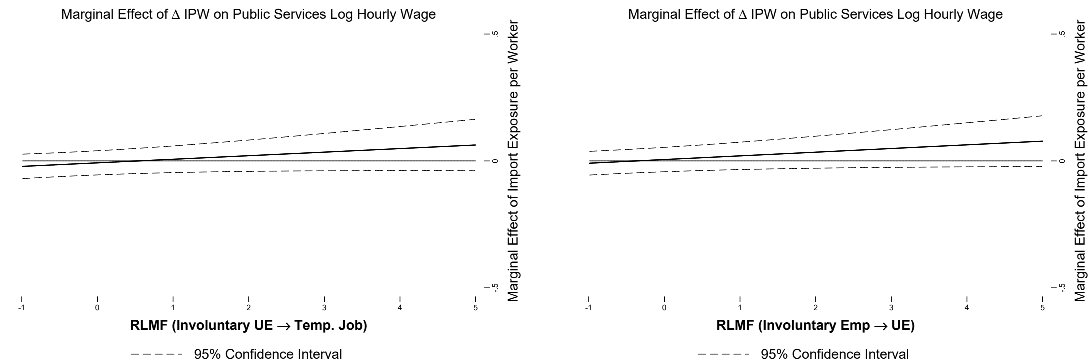
Figure 4.12: Marginal Effects of Import Exposure per Worker on Construction Wages conditional on Regional Labor Market Frictions



The marginal effects plots show the response of construction hourly wages to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.B3.

the trade shock in terms of employment, there is no visible reaction in terms of wages, independent of the level of labor market frictions. Two potential explanations are possible. First, there might be a downward bias of wage in public services, especially if less-skilled workers enter this sector after displacement in the manufacturing sector. The second explanation is that public wages are independent of local shocks, and rather subject to national developments.

Figure 4.13: Marginal Effects of Import Exposure per Worker on Public Services Wages conditional on Regional Labor Market Frictions



The marginal effects plots show the response of construction hourly wages to Chinese import competition (Δ IPW). The left panel uses the involuntary inflow from unemployment as a measure of regional labor market frictions (RLMF Involuntary UE → Temp. Job), while the right panel uses the involuntary outflow from temporary employment to unemployment (RLMF Involuntary Emp → UE). Results are based on the IV treatment of the interaction, i.e. columns (5) and (6) of table 4.B4.

The difference in wages in manufacturing compared to Autor et al. (2013) can have three different reasons. First, this paper uses log hourly wages instead of log weekly wages, which can lead to differences in results due to hours worked per week. Second, wage cuts are much less frequent in Europe compared to the United States. Downward nominal rigidity is typically not comparable over countries due to different data, estimations and time periods used, but Holden (2004) and references therein argue that the requirement of mutual consent for wage cuts is not given in the United States, which increases the occurrence of wage reductions considerably. Third, the upward bias could stronger in Europe, which is the case if increased import competition affects low-skilled workers in Europe more adversely than in the United States.

The combination of the employment effects being larger for Europe - even with average labor market frictions - compared to the findings by Autor et al. (2013) and no negative impact on log hourly wages in seems to point at the second explanation. This indicates that employers in the United States can adjust in terms of both employment and wages, while employers in Europe have to adjust more in terms of employment due to stronger downward nominal wage rigidity and the lesser extent of acceptance of wage cuts. However, more detailed data on employment losses across different skill groups is necessary and requires more detailed data on skill type and hours worked.

4.3.4 Robustness analyses

The robustness analysis of this paper focuses on the results for employment shares because the results for wages are not statistically significant. To test for the validity of the baseline results shown above, this paper applies sensitivity analyses that are similar to those of previous studies, such as Autor et al. (2013) and Colantone and Stanig (2017). They mainly focus on various modifications to the definition of the regional trade shock described in equations 4.1 and 4.2. Tables 4.C1 to 4.C6 in the appendix exploit net imports from China instead of realized imports in order to account for potential gains from exports, which were highlighted by Feenstra and Sasahara (2018), especially for the service sector. The point estimate of the constitutive term of the trade shock per worker, which measures the impact on manufacturing employment conditional on average labor market friction, drops slightly (to .99 on average) in this robustness analysis. This does indicate gains from exports to China in terms of manufacturing employment. However, only Germany experiences a rise in exports of manufacturing goods to China over the time horizon under scrutiny, which is an alternative to the findings by Dauth et al. (2017). The point estimates of the other variables of interest are largely unchanged. Further, the F-Statistic for all first-stage regressions is still very high and the explained variation of the instrumented variable always exceeds 67%.

For the services and the construction sector, the results are qualitatively unaltered. All six specifications exhibit noisy estimates of the import shock on services employment share conditional on average labor market friction. This is not necessarily contradictory to the findings of Feenstra and Sasahara (2018) as other advanced countries probably constitute

the destination of US service exports. For the construction sector, the average of the point estimates - given the mean use of temporary contracts - rise compared to the baseline results and equal the losses in the manufacturing (in absolute terms). The estimates for the interaction terms are more noisy in some cases, but are qualitatively unchanged with one exception. Similar to the manufacturing sector, all first stage regressions exhibit large F-values and explain the variation of both the EU net import shock and its interaction with labor market frictions well.
The second modification to the instrument of the import shock with bilateral trade data between the European economies and China is to use import data of other advanced economies, excluding the US. As previous research, this paper undertakes this sensitivity analysis for two reasons. First, because Chinese exports to the US might have been different compared to other advanced economies, and second because US imports from China were much larger in the period under consideration, which would yield - by definition - very similar results to the baseline approach. The results for all sectors and non-employment alternatives displayed in the appendix, i.e. in Tables 4.D1 to 4.D6. In this case, over all six specifications, the average decline of manufacturing to a \$ 1,000 rise in import competition from China is equal to 1.01, conditional on average labor market friction. This value is just in between the baseline analysis and the previous sensitivity analysis with net imports. The point estimates of the constitutive term of import exposure for the service sector are also slightly increasing relative to the benchmark results, and now three out of six specifications exhibit statistical significance on at least one of the conventional levels. The point estimates for the construction sector, on the other hand, are unchanged compared to the baseline results discussed above. For all estimations, regardless of the sector and the identification strategy, the conditional responses are qualitatively unchanged, as well as the instruments are also considered strong for all first-stage regressions.

4.4 Conclusion

This study builds on the notion of previous studies that the quantitative adjustment in the employment share of the manufacturing sector may differ with institutional labor market settings. Based on the same literature, this paper applies an instrumental variable estimation approach to measure the supply-driven import exposure to Chinese goods of regional labor markets in eight European economies. It then investigates the conditional response of employment shares in manufacturing to labor market frictions. The study introduces two measures of regional labor market frictions building on the idea that temporary contracts are more common in rigid labor markets as the costs associated with permanent contracts are too high. Both indicators exploit the flow between involuntary temporary jobs and unemployment, one for each direction. The identification strategy accounts for the idea that the conditional response, i.e. the interaction term of regional import exposure and labor market frictions, is endogenous as well and applies three different estimation approaches. Further, it extends the analysis to other sectors of employment, namely services, construction and non-market services, and to both the unemployment and labor force participation rate.

The results confirm the idea that labor market frictions exacerbate the magnitude of the impact of the trade shock on job losses in the manufacturing sector. In other words, with a higher adoption rate of temporary contracts due to high labor market frictions, employment shares in manufacturing decline even stronger when facing an adverse trade shock. Especially in more frictional labor markets, where the decline in manufacturing is stronger, it is important to determine what happens to displaced workers. The services sector only shows a noisy increase in employment shares relative to the import shock, whereas the construction sector is unresponsive to the trade shock. Instead non-market services, which includes health and education, absorbs the adverse impact. Considering non-employment alternatives, the unemployment rate does not rise across Europe due to the trade shock. If anything, its response is negative. The labor force participation rate tends to fall with rising competition from China, and is also exacerbated with labor market frictions. Probably, older workers advance retirement and exit the labor force. However, the results are estimated with noise and to verify this hypothesis would require more detailed data.

In all sectors, wages do not respond to import competition from China irrespective of the level of labor market frictions. Downward nominal wage rigidity is a potential explanation for these observations, in particular for the manufacturing sector because it is adversely affected by the trade shock. This could explain the stronger response of employers in terms of employment across Europe relative to the United States. The findings in this study for Europe of no rising wages in non-manufacturing sectors provides evidence against the "option value" in Artuç et al. (2010), where workers in the import-competing sector can benefit from liberalization due to rising real wages in other sectors than manufacturing.

Policymakers should try to reduce the adverse impact of trade shocks from low-wage countries on manufacturing by reducing labor market frictions. When considering the adoption of temporary contracts, several options are available: First, employment protection for temporary workers could be raised again, which, as theory suggests, would probably be associated with a loss in overall employment rates. Second, a reduction in the employment protection of permanent contracts, which would raise uncertainty on the worker's side. A third option is a wage premium for temporary contracts due to higher uncertainty and flexibility, which would also reinforce the original idea of temporary contracts, namely to allow firms to adjust to demand shocks. The policy needs to be well designed such that entrance for groups who use temporary contracts to get access to the

labor market, such as young and returning workers, is not jeopardized.
Finally, to account for the losers of adverse trade shocks, policymakers have two main options. First, moving subsidies and retraining. Dix-Carneiro (2014) shows for Brazil that the former is more relevant than the latter. However, the question is whether this holds for Europe or the United States given the structural changes in terms of employment structures in advanced economy, in particular the rise of the service sector.

4.A Manufacturing Subsectors

Table 4.A1: Manufacturing subsectors for trade exposure

NACE	Industry Description
DA	Manufacture of food products, beverages and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD	Manufacture of wood and wood products
DE	Manufacture of pulp, paper and paper products; publishing and printing
DF	Manufacture of coke, refined petroleum products and nuclear fuel
DG	Manufacture of chemicals, chemical products and man-made fibers
DH	Manufacture of rubber and rubber products
DI	Manufacture of other non-metallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK	Manufacture of machinery and equipment n.e.c.
DL	Manufacture of electrical and optical equipment
DM	Manufacture of transport equipment
DN	Manufacture n.e.c.

4.B Regression Results Log Hourly Wages

Table 4.B1: Conditional effect of import exposure on manufacturing log hourly wage

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.05	0.01	-0.04	-0.03	0.05	0.02
	(1.09)	(0.43)	(-0.85)	(-0.87)	(1.24)	(0.44)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.01		0.01		0.02	
	(0.79)		(0.29)		(1.39)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.03^{**}		0.02		0.02^{**}
		(2.16)		(0.70)		(2.43)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02^{***}	0.03^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
	(4.99)	(6.00)	(5.05)	(5.44)	(5.21)	(5.32)
R^2	0.63	0.71	0.71	0.71	0.63	0.64
F-Statistic	24.92	35.96	25.49	29.60	27.10	28.32
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04^{***}	
					(7.39)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05^{***}
						(13.43)
R^2			0.75	0.76	0.80	0.91
F-Statistic			2.33	3.89	54.54	180.39

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in manufacturing log hourly wage. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.B2: Conditional effect of import exposure on services log hourly wage

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.07*	0.05**	0.02	0.04	0.07**	0.06**
	(1.95)	(1.97)	(0.78)	(1.46)	(2.29)	(1.98)
RLMF (Involuntary Emp $\rightarrow$ UE) $\times$ Δ IPW (EU)	-0.00		-0.02		0.01	
	(-0.20)		(-1.09)		(0.63)	
RLMF (Involuntary UE $\rightarrow$ Temp. Job) $\times$ Δ IPW (EU)		0.03**		-0.01		0.02*
		(2.16)		(-0.59)		(1.78)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02***	0.03***	0.02***	0.02***	0.02***	0.02***
	(4.98)	(5.96)	(5.20)	(5.65)	(5.20)	(5.30)
R^2	0.63	0.71	0.70	0.70	0.63	0.64
F-Statistic	24.77	35.54	27.04	31.89	27.00	28.14
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp $\rightarrow$ UE) $\times$ Δ IPW (US)					0.04***	
					(7.25)	
RLMF (Involuntary UE $\rightarrow$ Temp. Job) $\times$ Δ IPW (US)						0.05***
						(13.37)
R^2			0.75	0.76	0.80	0.91
F-Statistic			3.12	3.31	52.61	178.82

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in services' log hourly wage. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.B3: Conditional effect of import exposure on construction log hourly wage

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.05	-0.00	0.01	-0.03	0.06	-0.00
	(1.26)	(-0.11)	(0.16)	(-0.81)	(1.57)	(-0.13)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.02		0.06^{*}		0.02	
	(0.92)		(1.92)		(1.47)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.04^{**}		0.02		0.04^{***}
		(2.51)		(0.66)		(2.97)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
	(5.01)	(6.00)	(4.93)	(5.28)	(5.23)	(5.34)
R^2	0.64	0.71	0.70	0.70	0.64	0.64
F-Statistic	25.15	35.95	24.34	27.87	27.35	28.55
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04^{***}	
					(7.14)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05^{***}
						(13.46)
R^2			0.75	0.74	0.80	0.91
F-Statistic			3.76	2.78	51.01	181.21

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in construction log hourly wage. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.B4: Conditional effect of import exposure on public services log hourly wage

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.01	-0.00	-0.03	-0.02	0.01	-0.01
	(-0.28)	(-0.19)	(-1.25)	(-0.66)	(0.22)	(-0.31)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.00		-0.01		0.01^{*}	
	(-0.00)		(-0.40)		(1.85)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.01		0.01		0.01^{*}
		(0.85)		(0.32)		(1.66)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (US)	0.02^{***}	0.03^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
	(5.04)	(5.99)	(5.11)	(5.50)	(5.26)	(5.36)
R^2	0.64	0.72	0.70	0.70	0.64	0.64
F-Statistic	25.44	35.89	26.10	30.23	27.69	28.76
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (US)					0.04^{***}	
					(7.15)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (US)						0.05^{***}
						(13.26)
R^2			0.75	0.74	0.80	0.91
F-Statistic			2.66	3.14	51.19	175.81

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in public services' log hourly wage. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using US imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

4.C Robustness Results for Employment - Net Import Exposure

Table 4.C1: Conditional effect of net import exposure on manufacturing employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	-1.02**	-0.34	-1.62***	-1.43***	-1.17**	-0.30
	(-2.12)	(-1.27)	(-4.46)	(-4.04)	(-2.27)	(-1.03)
RLMF (Involuntary Emp → UE) × Δ NPW (EU)	-0.31*		-0.55*		-0.50**	
	(-1.92)		(-1.95)		(-2.47)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (EU)		-0.66***		-0.15		-0.73***
		(-3.19)		(-0.52)		(-3.44)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(6.04)	(7.29)	(6.47)	(6.31)	(6.33)	(6.44)
R^2	0.67	0.71	0.74	0.74	0.68	0.67
F-Statistic	36.43	53.09	41.89	39.78	40.07	41.50
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ NPW (US)					0.04***	
					(8.20)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (US)						0.05***
						(12.88)
R^2			0.74	0.75	0.82	0.93
F-Statistic			3.40	3.39	67.25	165.86

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in manufacturing employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.C2: Conditional effect of net import exposure on services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	0.00	-0.21	1.31**	0.50	0.14	-0.32
	(0.01)	(-0.40)	(2.33)	(0.89)	(0.29)	(-0.52)
RLMF (Involuntary Emp → UE) × Δ NPW (EU)	0.10		1.59**		0.31	
	(0.59)		(2.49)		(1.29)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (EU)		0.31		-0.28		0.55**
		(1.19)		(-0.31)		(2.02)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02***	0.03***	0.02***	0.03***	0.02***	0.02***
	(6.64)	(7.50)	(7.10)	(7.00)	(6.93)	(6.89)
R^2	0.65	0.69	0.71	0.72	0.65	0.65
F-Statistic	44.08	56.23	50.35	48.99	48.09	47.48
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ NPW (US)					0.04***	
					(8.37)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (US)						0.05***
						(12.95)
R^2			0.74	0.74	0.83	0.92
F-Statistic			2.51	3.05	70.06	167.68

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.C3: Conditional effect of net import exposure on construction employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	-0.17	-0.08	-0.19	-0.09	-0.21	-0.03
	(-1.18)	(-0.71)	(-1.03)	(-0.60)	(-1.45)	(-0.24)
RLMF (Involuntary Emp → UE) × Δ NPW (EU)	-0.05		0.00		-0.11	
	(-0.71)		(0.03)		(-1.60)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (EU)		-0.19***		-0.39**		-0.30***
		(-2.73)		(-2.16)		(-4.05)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02***	0.03***	0.03***	0.03***	0.02***	0.02***
	(6.91)	(7.61)	(7.88)	(7.91)	(7.03)	(7.16)
R^2	0.67	0.70	0.72	0.72	0.67	0.67
F-Statistic	47.77	57.96	62.04	62.50	49.45	51.22
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ NPW (US)					0.04***	
					(8.39)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (US)						0.05***
						(13.25)
R^2			0.74	0.77	0.83	0.93
F-Statistic			3.60	2.07	70.42	175.68

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in construction employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.C4: Conditional effect of net import exposure on public services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	0.78**	0.58*	0.77***	0.26	0.79**	0.67*
	(1.98)	(1.72)	(2.79)	(0.84)	(2.21)	(1.89)
RLMF (Involuntary Emp → UE) × Δ NPW (EU)	-0.07		0.38		-0.07	
	(-0.55)		(1.56)		(-0.41)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (EU)		0.50***		1.38***		0.31**
		(3.44)		(4.12)		(2.47)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02***	0.03***	0.02***	0.03***	0.02***	0.02***
	(6.60)	(7.34)	(6.93)	(7.04)	(6.82)	(6.72)
R^2	0.65	0.69	0.71	0.71	0.65	0.65
F-Statistic	43.56	53.82	48.04	49.58	46.49	45.22
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ NPW (US)					0.04***	
					(8.19)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (US)						0.05***
						(13.10)
R^2			0.74	0.76	0.83	0.93
F-Statistic			3.97	3.25	67.15	171.49

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in public services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.C5: Conditional effect of net import exposure on unemployment rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	-0.73	0.76**	-2.38	-2.77	-0.94	-1.17
	(-0.47)	(2.03)	(-1.30)	(-1.35)	(-0.64)	(-0.76)
RLMF (Involuntary Emp → UE) × Δ NPW (EU)	0.77		0.04		0.45	
	(1.16)		(0.03)		(0.75)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (EU)		0.54***		3.05		-0.67
		(3.22)		(1.58)		(-1.25)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02***	0.03***	0.02***	0.03***	0.02***	0.02***
	(6.75)	(7.61)	(7.15)	(6.81)	(6.99)	(6.95)
R^2	0.65	0.69	0.71	0.71	0.66	0.66
F-Statistic	45.50	57.98	51.16	46.38	48.88	48.32
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ NPW (US)					0.04***	
					(8.26)	
RLMF (Involuntary UE → Temp. Job) × Δ NPW (US)						0.05***
						(12.87)
R^2			0.75	0.74	0.82	0.92
F-Statistic			3.19	2.37	68.20	165.76

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in the unemployment rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.C6: Conditional effect of net import exposure on labor force participation rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ NPW (EU)	-0.77	0.71^{*}	-1.06	-0.78	-0.76	-0.04
	(-0.85)	(1.87)	(-1.32)	(-1.06)	(-0.91)	(-0.05)
RLMF (Involuntary Emp $\rightarrow$ UE) $\times$ Δ NPW (EU)	-0.56		-0.71		-0.54	
	(-1.49)		(-0.93)		(-1.24)	
RLMF (Involuntary UE $\rightarrow$ Temp. Job) $\times$ Δ NPW (EU)		0.51^{***}		0.07		-0.83^{**}
		(3.14)		(0.06)		(-2.32)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ NPW (US)	0.02^{***}	0.03^{***}	0.03^{***}	0.03^{***}	0.02^{***}	0.02^{***}
	(6.76)	(7.57)	(7.95)	(7.70)	(7.03)	(6.95)
R^2	0.65	0.69	0.70	0.71	0.65	0.65
F-Statistic	45.74	57.32	63.13	59.29	49.42	48.26
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp $\rightarrow$ UE) $\times$ Δ NPW (US)					0.04^{***}	
					(8.26)	
RLMF (Involuntary UE $\rightarrow$ Temp. Job) $\times$ Δ NPW (US)						0.05^{***}
						(12.96)
R^2			0.75	0.74	0.83	0.92
F-Statistic			3.22	2.07	68.29	167.92

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in labor force participation rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral net imports of EU countries using US net imports from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

4.D Robustness Results for Employment - Other Advanced Countries

Table 4.D1: Conditional effect of import exposure on manufacturing employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-1.19**	-0.32	-1.50***	-1.34***	-1.44**	-0.22
	(-1.98)	(-1.16)	(-4.29)	(-4.04)	(-2.24)	(-0.63)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.22		-0.34		-0.42***	
	(-1.61)		(-1.62)		(-2.59)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.52***		-0.14		-0.61***
		(-2.84)		(-0.55)		(-3.38)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.02***	0.03***	0.02***	0.02***	0.02***	0.02***
	(3.79)	(5.19)	(3.67)	(3.79)	(4.10)	(4.35)
R^2	0.67	0.74	0.74	0.74	0.67	0.68
F-Statistic	14.37	26.91	13.43	14.35	16.82	18.93
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(6.89)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.06)
R^2			0.75	0.75	0.79	0.91
F-Statistic			3.60	3.96	47.44	145.41

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in manufacturing employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.D2: Conditional effect of import exposure on services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.12	-0.10	1.19**	0.39	0.29	-0.23
	(0.22)	(-0.22)	(2.39)	(0.92)	(0.61)	(-0.41)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.06		1.25**		0.25	
	(0.45)		(2.43)		(1.29)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.27		-0.11		0.49**
		(1.00)		(-0.17)		(2.12)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.03***	0.04***	0.03***	0.03***	0.03***	0.03***
	(5.21)	(5.95)	(4.53)	(4.70)	(5.40)	(5.42)
R^2	0.64	0.72	0.71	0.71	0.64	0.64
F-Statistic	27.19	35.36	20.55	22.10	29.11	29.39
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(7.12)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.15)
R^2			0.75	0.74	0.80	0.90
F-Statistic			2.58	2.90	50.75	147.60

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.D3: Conditional effect of import exposure on construction employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.17	-0.09	-0.15	-0.11	-0.22	-0.01
	(-1.16)	(-0.81)	(-0.87)	(-0.81)	(-1.47)	(-0.12)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.03		0.07		-0.09	
	(-0.53)		(0.51)		(-1.47)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.15**		-0.30**		-0.26***
		(-2.43)		(-2.01)		(-4.29)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.03***	0.04***	0.03***	0.04***	0.03***	0.03***
	(5.44)	(6.02)	(5.65)	(5.91)	(5.47)	(5.70)
R^2	0.66	0.72	0.71	0.71	0.66	0.66
F-Statistic	29.56	36.19	31.90	34.90	29.88	32.47
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(7.08)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.64)
R^2			0.75	0.77	0.79	0.91
F-Statistic			3.70	1.60	50.11	159.75

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in construction employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.D4: Conditional effect of import exposure on public services employment shares per working-age population

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	0.85**	0.51*	0.52**	0.37	0.85**	0.67*
	(2.04)	(1.71)	(2.05)	(1.40)	(2.27)	(1.93)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.06		0.18		-0.06	
	(-0.50)		(0.96)		(-0.37)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		0.53***		1.14***		0.29***
		(3.32)		(4.28)		(2.59)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.03***	0.04***	0.03***	0.03***	0.03***	0.03***
	(5.01)	(5.76)	(4.60)	(4.90)	(5.18)	(5.19)
R^2	0.64	0.72	0.70	0.70	0.64	0.64
F-Statistic	25.11	33.23	21.16	23.97	26.87	26.93
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(6.92)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.14)
R^2			0.75	0.75	0.79	0.90
F-Statistic			4.19	3.64	47.82	147.32

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in public services employment share per working-age population. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.D5: Conditional effect of import exposure on unemployment rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.73	-1.11	-3.80*	-3.36	-0.97	-1.07
	(-0.46)	(-0.84)	(-1.91)	(-1.55)	(-0.64)	(-0.71)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	0.65		-0.39		0.38	
	(1.21)		(-0.41)		(0.73)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.63		2.75*		-0.69
		(-0.94)		(1.70)		(-1.41)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.03***	0.04***	0.03***	0.03***	0.03***	0.03***
	(5.19)	(5.92)	(4.81)	(4.79)	(5.34)	(5.37)
R^2	0.64	0.72	0.70	0.70	0.64	0.65
F-Statistic	26.93	35.07	23.17	22.96	28.47	28.84
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(6.92)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.09)
R^2			0.75	0.73	0.79	0.90
F-Statistic			3.42	2.47	47.85	146.11

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in the unemployment rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Table 4.D6: Conditional effect of import exposure on labor force participation rate

Treatment of Interaction Term	OLS		Functional		IV	
I. Second-stage 2SLS Estimates	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW (EU)	-0.62	0.05	-0.89	-0.66	-0.61	0.17
	(-0.68)	(0.08)	(-1.28)	(-1.11)	(-0.74)	(0.23)
RLMF (Involuntary Emp → UE) × Δ IPW (EU)	-0.43		-0.53		-0.42	
	(-1.33)		(-0.91)		(-1.14)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (EU)		-0.50		0.18		-0.69**
		(-1.19)		(0.21)		(-2.21)
Observations	292	292	292	292	292	292
II. First-Stage Estimates						
Δ IPW (OTH)	0.03***	0.04***	0.03***	0.04***	0.03***	0.03***
	(5.29)	(5.97)	(5.81)	(5.88)	(5.47)	(5.46)
R^2	0.64	0.72	0.70	0.70	0.64	0.64
F-Statistic	28.00	35.67	33.72	34.53	29.87	29.82
III. First-Stage Estimates (Interaction Term)						
RLMF (Involuntary Emp → UE) × Δ IPW (OTH)					0.06***	
					(6.95)	
RLMF (Involuntary UE → Temp. Job) × Δ IPW (OTH)						0.08***
						(12.17)
R^2			0.75	0.73	0.79	0.90
F-Statistic			4.02	2.01	48.35	148.02

Notes: The dependent variable of the second stage of the 2SLS approach in panel I is the change in labor force participation rate. Both modifying variables measure regional labor market frictions are standardized. All specifications instrument for endogenous bilateral imports of EU countries using imports of other advanced economies, i.e. Australia, Canada, Korea, Japan and New Zealand, from China as an instrument. Panel II presents the estimation results for all specifications for this first-stage. Columns (1) and (2) report results for the estimation approach, where the interaction term is taken as exogenous. Columns (3) and (4) show the results for the identification strategy, which instruments for the interaction term exploiting a vector of second-order polynomials of the control variables and the conditioning variable. Due to the size of the vector and the non-economic nature of these estimates, the results are not shown in panel III. Columns (5) and (6) display the results of the approach, which instruments for the interaction term using the interaction of the instrument for the endogenous explanatory variable and the modifying variable. The results are shown in panel III. Standard errors are clustered on the regional level. 95% confidence intervals in brackets. *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance.

Chapter 5

General Conclusion

This dissertation presents three essays at the intersection of labor economics and macroeconomics. It shows that macroeconomic events and developments have substantial impact on labor market outcomes of workers. The first two essays tackle widely discussed trends in advanced economies, namely globalization of goods and automation of routine labor. The former gained importance in the public and academic debate with the rise of China in global commodity markets since its entry to the WTO in 2001, while the latter is a more gradual process due to increasingly declining costs for ICT capital. These two essays also take on a regional perspective and determine how these macroeconomic developments differ across space. The first and third essay also consider institutional settings and how they affect labor market outcomes. The first essay exploits involuntary labor reallocation in and out of temporary employment, which is likely due to high employment protection for permanent contracts. The third essay examines the impact of institutional settings, in particular the wage bargaining regime and family policy, on two different components of the gender wage gap.

Chapter 2 explores the impact of labor market polarization, triggered by rising automation of routine-intensive tasks, on intergenerational mobility. The essay first builds an overlapping generations model with spatial heterogeneity and the task framework with three occupations, and it provides multiple predictions with respect to educational choice and intergenerational elasticity by parental background and upward mobility for children from low-income parents. Falling (computer) capital prices serve as an exogenous shock in the model. As educational choice depends on parental bequests and future wage ratios, children whose parents work in either manual or abstract occupations, increasingly tend to choose the education which allows them to enter the same occupation as their parents. The opposite holds for children whose parents work in routine occupations as the demand for routine employment falls with rising automation. The different rates of cross-generational transitions in occupations imply distinct patterns in intergenerational elasticity. For children with parents in manual and abstract occupations, the decrease in transitions entails higher intergenerational elasticity, whereas it implies lower one for children with parents in routine occupations. Ultimately, the model predicts lower upward mobility for children from low-income families.

The essay tests the model predictions with various data sources for the United States. Education polarization of young labor market entrants increases over time, and the strongest rise coincides with the timing of the IT revolution, i.e. between 1990 and 2000. Family premia for various educational levels based on PSID data indicate that especially children of parents with a college degree also tend to get a college degree. The essay also investigates intergenerational mobility with the PSID, and confirms the pattern predicted by the model. The pattern arises over time, which is particularly driven by declining and rising elasticity for children from parents with routine and abstract occupations, respectively. Finally, the empirical evidence also supports the model prediction for upward mobility of children from low-income families on the commuting-zone level using an instrumental variable estimation strategy. The instruments are historical (log) density and routine employment, which are based on the model and previous literature.

The results of the first essay pose multiple research questions. What is the impact on tuition fees on college education and dropouts? The first relates to the choice to start college education, the latter refers to finishing college, which might not be possible due to a lack of ability or struggling finances. How reliable are college gradients for predicting future upward mobility if the overall society is upskilling and high college dropout rates as in the United States? In terms of external validity, similar studies for European countries are possible, where regional differences in labor market polarization and upward mobility are also likely to occur. The main difference between the United States and continental Europe are much lower costs for tertiary education in the latter, and even general financial support for tertiary education in Scandinavian countries. Therefore, labor market polarization might not have the same detrimental impact on intergenerational elasticity or upward mobility in Europe.

Chapter 4 investigates whether labor market frictions impact the response to Chinese import competition on the regional level in eight European countries. It exploits involuntary reallocation in and out of temporary employment to measure regional labor market frictions. The essay's first main finding shows that labor market frictions exacerbate the detrimental impact of Chinese exports on manufacturing employment. In other words, the stronger labor market frictions are, regardless of their measure and the treatment of the interaction term due to its endogeneity, the stronger the decline in manufacturing workers. In order to understand what employment or non-employment alternatives the displaced workers choose, the essay repeats the same analysis for other sectors of economic activity, the unemployment rate and the labor force participation rate. The second main finding of the essay is that public services tends to absorb the adverse impact on the manufacturing sector.

The second essay also provides both policy advice and further research questions. The main policy recommendation refers to the reduction of labor market frictions, which allows for labor reallocation of workers face to shocks. The design of these policies needs to ensure that it does not hurt a specific group such as young labor market entrants or returning workers. Further, both moving subsidies and retraining are potential candidates to enable workers to cushion the adverse shock. In terms of future research based on this, other labor market settings can be investigated, e.g. the wage bargaining regime. As wages are unresponsive to Chinese import competition, manufacturing employment could adjust stronger if collective bargaining is more centralized.

Chapter 3 examines how firms contribute to the gender wage gap in the form of firm-specific pay differentials for 21 European countries across 12 years. It decomposes this differentials into a within- and a between-firm component, and shows that both are nearly equally important for the full sample in 2014. The former component, however, is mainly responsible for the slow decline in the gender pay gap between 2002 and 2014, whereas the latter is driving the well-known increase in the pay gap across the life cycle. It rises in particular after family formation, and does not decrease thereafter. The essay associates each component with different institutional settings: the within-firm component with collective bargaining regimes, and the between-firm component with family policy. The paper does not claim any causal evidence, but suggests that the within-firm gender wage gap does not fall with more centralized wage bargaining even though an extensive literature has shown that it reduces overall wage inequality. Finally, higher family various indicators of family policy, e.g. spending in services, higher enrolment in pre-education programs and length of maternity leave, seem to have an impact on the gender wage gap. While the first two reduce the gender wage gap for multiple age groups after family formation, i.e. after 30 to 39, the latter raises it. Importantly, the essay does not find a similar impact on the youngest age group.

The policy suggestions from our findings are quite obvious based on the findings relating to institutional settings. Family policy has the potential to reduce the strong rise of the gender wage gap across the life cycle. However, the findings from this part of the analysis are tentative and more research on the impact on family policy is required, especially due to its complexity. One interesting aspect is paternity leave, which lacks extensive applications, and therefore thorough research. However, the paper also offers various questions, especially related to spatial heterogeneity. Do women tend to work in different firms both in cities and more rural areas? Is the rise in the gender wage gap - in total or driven by the between-firm component - after family formation similar across locations? As cities offer more service-intensive jobs, this might have an impact on the gender wage gap across the life cycle.

Overall, the intersection of labor economics and macroeconomics is multi-faceted and offers many interesting research questions. While this dissertation focuses mainly on labor market outcomes of workers and young labor force entrants, it disregards adjustment processes of firms to macroeconomic developments. Further, the paper largely focuses on long-term developments, whereas crises tend to be catalysts for faster structural transformation. More disaggregated data in the form of labor force surveys, vacancy postings, and both administrative and matched employer-employee data sets allows researchers to better understand how both long-term trends and macroeconomic shocks affect labor market outcomes. In the future, the spatial perspective will gain importance for research at the intersection of labor economics and macroeconomics.

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