On the Link between Job Polarisation and Wage Inequality – A regional approach for Germany

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This version: April 21, 2016

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Abstract

Rich countries experience job polarisation and rising wage inequality in the past decades. Evidence on a link between both events is inconclusive. I benefit from regional variation in job polarisation to assess the impact of job polarisation upon wage inequality in Germany. The rise in wage inequality extends with larger job polarisation. I show how these differentials in wage inequality are explained by regional diversity in the workforce compostion. It cannot be explained by job polarisation itself. Job polarisation relates to increasing skill shifts within occupations, explaining the prima facie but spurious relationship between job polarisation and wage inequality.

Keywords: polarisation, wage inequality, regions, distributional decomposition
JEL Classification: J31

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I Introduction

Wage inequality and job polarisation are thoroughly analysed in labour market literature. Wage inequality refers to the wage dispersion. Wage inequality describes the relative rise of wages in top-paying jobs relative to low-paying jobs (Acemoğlu and Autor, 2011). Job polarisation describes the relative decline in the share of medium-paying jobs relative to top- and bottom-paying jobs (Goos and Manning, 2007). Rising wage inequality and job polarisation both appear in Germany (Dustmann et al., 2009).

Both phenomena are closely linked to technological change. The rise in workers' productivity due to technological change rises with the workers' skills (Katz and Murphy, 1992). It induces wage inequality, i.e. larger wage growth for high-skilled workers than low-skilled workers, when demand growth due technological change exceeds educational expansion (Tinbergen, 1975). Job poloarisation is closely linked to technological change in Information and Communication Technologies, for example the increasing speed at which computers can perform tasks. Computers can substitue codifiable routine tasks, typically medium-paying, and complement uncodifiable abstract tasks, typically top-paying, while their impact upon low-paying jobs is limited (Autor et al., 2003). The rise of computer capital and its growing impact upon occupational shifts only began in the late 1980s (Autor et al., 2008).

There is evidence for a direct link between technological change and wage inequality in the U.S. (Autor et al., 2008; Katz and Murphy, 1992). The stability of the German wage structure until the mid-1990s instanced against this conjecture (Beaudry and Green, 2003; Prasad, 2004). Notwithstanding, since the mid-1990s, also German wage inequality has risen (Dustmann et al., 2014; Kohn, 2006). Since wage decompression has finally started, the question arises whether this rise in wage inequality can be linked to job polarisation.

The impact of job polarisation upon wage inequality consists of a quantity and a wage effect. Job polarisation mechanically drives up wage inequality, since the quantity of top-paying and bottom-paying jobs increases. Besides, employment polarisation may also influence wages within occupations or the return to skills. The direction of the latter link is not a priori clear. Changes in employment may be driven by changes in the demand for workers by occupation. The increased demand in high- and low-paying occupations induces upper and lower tail wages to rise, while the demand and wages for medium-paying occupations falls (Autor et al., 2008; Katz and Murphy, 1992). The relationship then is positive. Occupational changes may also be supply-driven. Occupational upgrading may lag behind the expansion of higher education, pushing down high-skilled workers in lower positions and creating an oversupply of skills associated with wage erosion (Åberg, 2003; Beaudry et al., 2014). In a similar vein, displaced medium-skilled workers in routine occupations orientate downwards and create an oversupply in these occupations, causing an erosion of wages at the bottom. At the same time, medium-paying job's wages are lifted, since the most talented and productive workers are not displaced. The relationship then is negative. Lastly, technological change may also increment skill requirements within occupations, leading to rising productivity, and eventually rising wages. The direct relationship then is unclear, and both wages and employment depend upon the skill formation within occpations rather than employment shifts.

This study shows that skills as well as skills shifts within occupations are an essential driver of the employment and skills, while there is no direct link between job polarisation and wage inequality. The link is assessed by two methods, which should be interpreted seperately. The first includes an innovative approach, in which regional variation in job polarisation is used for identification. The results suggest that job polarisation and wage inequality occur concurrently, but are hardly linked to one another. Job polarisation increases wage inequality mechanically, while the price effect is small and limited to upper tail wage inequality. Regional differentials in the workforce composition and skill formation almost fully explain altering patterns in the rise of wage inequality. The second approach extends the approach by Autor et al. (2008), who find a positive link between occupational and wage growth applying OLS regressions. I include skills and skill shifts within occupations as further explanatory variables to this regression. Once accounting for skills, the positive link between occupational and wage growth fully vanishes.

Section II discusses literature on wage inequality, job polarisation and its link internationally and in Germany. It also introduces literature on regional wage inequality and job polarisation. Section III describes the data and trends in labour market outcomes in Germany as well as its regions. The analysis on the link between wage inequality and job polarisation is conducted in section IV. Section V concludes the paper.

II Literature

II.1 International Literature

There are mainly two approaches that have sought to explain recent changes in rich countries' labour market outcomes that both rely heavily on technological change: Skill-biased and routine-biased technological change. The first approach, skill-biased technological change, aims at explaining monotonic relative labour demand growth along the skill distribution (Katz and Murphy, 1992). It is argued that technological change supplements workers with increasing skills, since they are more prone to adjust to new technologies (Tinbergen, 1975). Skill-biased technological change implies rising relative demand for high-skilled workers relative to the demand for low-skilled workers if not counterbalanced by educational expansion.

The impact of skill-biased technological change upon the wage structure became first empirically noticeable in the U.S. from the 1970s, when the expansion of high-skilled workers fell short of the technology-driven increasing demand (Goldin and Katz, 2009; Katz and Murphy, 1992). Relative employment and wages grew with increasing employment demand, i.e. with increasing skill level. This eventually causes rising wage inequality due to a strong positive link between employment and wage shifts.

The second approach, routine-biased technological change, came up with the emergence of Information and Communication Technologies (ICT), which caused altering patterns of occupational employment growth from the 1990s. Employment growth shifted to a u-curved pattern, in which relative growth of employment at both tails of the wage distribution outruns wage growth in the middle. It is closely associated with rising computer capital as well as the rising speed at which computers perform tasks. In contrast to skill-biased technological change that refers to workers' skills, it refers to workers' tasks. Autor et al. (2003) argue that computers are capable of performing codifiable routine tasks. Computer-based technologies hence substitute routine labour which is typically in the middle of the wage distribution. Their relative demand falls. At the same time, these technologies enhance productivity in abstract tasks that are typically performed in top-paying jobs. Productivity and labour demand in top-paying occupations then rises. The increase in computer capital has hardly any impact on tasks that are non-routine and manual, such as waiting a table or caring. These tasks are typically present in occupations at the bottom of the wage and skill distribution. These occupations, although not directly affected by technological change, nonetheless wittness increasing demand due to higher incomes of the high-skilled workers demanding these services and a necessity of regional proximity (Beaudry et al., 2012; Florida and Mellander, 2016; Leonardi, 2015; Moretti, 2010).

Goos and Manning (2007) introduced the term job polarisation by assessing occupational demand shifts in the UK. They empirically illustrate a u-curve of occupational growth, where the occupations' skills are proxied by the mean wage of a job. They further show how these shifts implied rising wage inequality. Autor et al. (2008) draws a direct link between occupational and wage shifts in the U.S. They illustrate how employment growth shifts from a monotonic pattern in employment growth until the end of the 1980s to a u-shaped pattern thenafter, which is mirrored by identical changes in wages.

Shifts in employment structure are universally observed in rich countries and are linked to Information and Communication technology. Michaels et al. (2014) confirm the polarisation hypothesis using industry-specific ICT investment as identification for occupational changes in the U.S., Japan and nine European countries, including Germany. They find that ICT investment is explanatory for changes in occupational shares, increasing the demand for top-paying and mitigating the demand for middle-paying occupations while having little impact upon low-paying occupations. Acemoğlu and Autor (2011) note that occupational shifts are comparable across numerous advanced labour markets, but shifts in the wage distribution differ. Cross-country differences reveal different responses to occupational shifts, which may lie in differences in the supply of labour, i.e. distinct growth paths in the supply and demand of high-skilled workers, but also distinct national regulations and legislations. Goos et al. (2009, 2014) investigate job polarisation in 16 European countries, including Germany, and confirm job polarisation as well as an increase in wage inequality. They confirm technological change as fruitful in explaining occupational shifts. Concurrently, they find no link between job polarisation and wage inequality in a cross-country analysis. Green and Sand (2014) similarly find evidence of job polarisation in Canada, while wage growth was monotonic, contrasting the view on a relationship.

II.2 Literature on German Wage Inequality and Job Polarisation

Job polarisation and the in rise wage inequality are also present in (West) Germany. The wage structure has comparably long been stable (Prasad, 2004). In comparison to the U.S. and the UK, the rise in wage inequality was less pronounced and only started to grow from the 1980s and was first limited to upper tail inequality (Dustmann et al., 2009). Dustmann et al. (2009) further find job polarisation applying a task approach. Abstract tasks are predominantly performed in top-paying occupations. Routine and manual tasks are performed both in the middle and lower tail of the wage distribution. Occupational changes slightly vary from the u-form. Although employment growth is similarly highest at the top, and declining in the middle, it is rather unchanged at the bottom. The pattern of occupational growth is rather j- than u-curved. Interestingly, Dustmann et al. (2009) depict these occupational shifts both for the 1980s, when wage inequality only raised at the upper tail, and the 1990s, when wage inequality raised at both tails. In both periods, occupational changes are similar, but changes in the wage distribution alter – suggesting no link between occupational and wage shifts. They propose other reasons that shape the wage distribution, such as supply shocks and changes in labour market institutions.

Spitz-Oener (2006) utilises four waves of the German Qualification and Career Survey for the years 1979, 1985/86, 1991/92, and 1998/99 to analyse job polarisation. The unique data set comprises individualised information on tasks, computer usage, etc. She finds support for routine-biased technological change in Germany. In particular, she finds increasing employment shares in low-paying non-routine manual tasks and top-paying non-routine cognitive task, as well as a declining employment shares in routine cognitive tasks. She directly links these shifts to computerisation.

Antonczyk et al. (2009) claim that the task approach by Spitz-Oener (2006) can only explain occupational shifts within the time period she observed. They extent the observed time horizon beyond 1999, analysing two waves of the Qualification and Career Survey in the years 1999 and 2006. Antonczyk et al. (2009) find declining employment shares in low-paying non-routine manual tasks, and a rise in medium-paying routine cognitive tasks – implying a reversal of job polarisation. This reversal is accompanied with a rise in wage inequality. They conclude 'changes in task assignments strongly work towards reducing wage inequality' and 'the task-based approach can not explain the recent increase of wage inequality in Germany' (Antonczyk et al., 2009, p. 214).

Beaudry and Green (2003) conduct a comparative analysis of the impact of technological change upon the labour market between the U.S. and Germany. Next to the evolution of human capital over time, they further take physical capital into account. They build a model in which the scarcity of physical capital is harmful for low-skilled workers in the course of technological change. They reason that the decrease of wages for the low-skilled workers in the U.S., while wages for the low-skilled grew in Germany, is due to divergent paths of physical capital formation between both countries. The U.S. faces an underaccumulation of physical relative to human capital, while Germany followed a balanced growth path. The abundant physical capital accumulation in Germany results in increasing wages for the lower-educated.

Freeman and Schettkat (2001) argue that differences in the degree of wage compression between the U.S. and Germany lie in the compression of skills in Germany. Other than the U.S., jobless workers in Germany have comparative skills to employed workers. The variance of skills in the U.S. is by contrast decompressed. Although they find that the compression of skills is a major driver of the larger inequality in the U.S., they also find institutional factors explanatory.

II.3 Literature on Wage Inequality and Job Polarisation using Regional Variation as Identification

The implementation of technological change and the resulting job polarisation is not spatially omnipresent within countries. Accetturo et al. (2014) enrich the canonical model proposed by Acemoğlu (2002) with a regional variation of skills. They show that the adoption of new technologies requires a certain regional skill level of the workforce. Skilled regions adopt new technologies faster and consequently further attract workers from less-skilled regions. Regional skill differentials diverge over time. Technical progress is subsequently regionally self-enforcing and path-dependent.

This phenomenon has also been observed empirically: Marinelli (2013) observes migration behaviour of Italian students at two points: At the beginning of their studies, and at the beginning of their first job. They find that students willing to migrate to study are also more willing to migrate after their studies. These students face a better skill-match due to a larger job market, and are also more concentrated in skilled regions. Consoli et al. (2013) find that graduates are generally prone to migrate to high-skilled regions. They further document that in times of rapid technological progess, migration to skilled regions similarly gains pace.

There further exist studies directly linking regional variation in technological change and job polarisation to the wage distribution. Florida and Mellander (2016) find higher wage inequality in U.S. counties with a greater concentration of high-technology industry. Workers in these counties have higher average skills. Employment in low-skilled jobs in these counties similarly grow faster, resulting in job polarisation. They find a positive correlation between wage inequality and high-technology as well as human capital formation. Yet, there are also hints that the higher average income in high tech counties narrows the wage distribution. They conclude that job polarisation is accompanied by wage inequality, but does not neccessarily imply wage inequality.

Autor and Dorn (2013) argue that U.S. commuting zones (CZ) that are initially specialised in routine jobs are more prone to computerisation, which eventually leads to higher job polarisation. Routine-intensive CZ face a steeper growth of employment and wages at the tails of the wage distribution, and a larger fall in employment in the middle. Lower tail wage growth counteracts the rise in wage inequality. They conclude that technical change and job polarisation do not need to enhance wage inequality.

In a similar vein, Beaudry et al. (2010) show that U.S. metropolitan areas with a high supply, i.e. low price, of high-skilled workers adopt computer technology faster. Demand for skills as well as returns to skills grow faster in these areas. They show that the implementation of new technologies, initially triggered by a relative oversupply of high-skilled workers, creates both job polarisation as well as wage inequality. Yet, Beaudry et al. (2012) report a positive effect on average wages in local labour markets that were subject to large employment growth in the high-wage sectors. Technological shocks lift overall wages due to general equilibrium effects

Lee et al. (2013) document similar findings for the UK. They descriptively analyse wage inequality and polarisation in British cities. The most polarised cities are the most unequal. The attraction of high-skilled workers induce wage inequality, but also improve labour market prospects of low-skilled workers. At the same time, the most equal cities have a small share of high-skilled workers, i.e. few high earners. These cities are overall poor. Average income and wage inequality are positively correlated.

All studies foreground one pattern: Polarised regions experience a larger rise in wage inequality. Still, no study suggests that (regional) job polarisation implies higher wage inequality.

III Data, Trends in Wage Inequality and Job Polarisation in Germany and its Regions

III.1 Data

This study grounds upon data of the Sample of Integrated Labour Market Biographies (SIAB) in Germany. These data were exploited in other studies to explore the German wage structure and the distribution of wages, e.g. Dustmann et al. (2009) and Card et al. (2013). Vom Berge et al. (2013) give a detailed description of the data set.

The SIAB is a 2 percent random sample of German social security records from 1975 to 2010 covering circa 11 million observations. It is drawn from the Integrated Employment Biographies Sample (IEB) of the Institute for Employment Research (IAB). Social security records are very reliable due to their administrative character. They contain information on all employments subject to social security contribution in Germany – which is roughly 80 % of the German workforce . Civil servants, self-employed, and soldiers are excluded from the data set since they are not subject to social security contribution.

The main limitation of the data is the right-censoring of the wage variable. Above a certain margin of income, the maximum social security contribution of an employer is reached. It does not increase with increasing income. The wage variable is fixed at that margin level for employees earning above the social security margin. This social security ceiling varies annually. As an example, it amounts to an annual income of €66,000 in the year 2010. This censoring affects roughly 10% of the wage variable of men and 2% of the wage variable of women with low annual variation. Measurement on wage inequality is typically measured as the 90th-10th interdecile range. The analysis here refers to the 85th and 15th percentile in order to circumvent censoring.

Wages are daily wages in the data set. Wages are those observed on June 30th for each year and each worker. Wages are inflation-adjusted regarding the consumer price indices from the federal office of statistics (Statistisches Bundesamt, 2016). Price indices are generally sensitive to quality change and new products (Moulton, 1996).

The analysis is restricted to workers with workplace and residence in West Germany, since East German data are only available after 1992. West Germany is referred to as Germany. Data is further limited to full-time employees, whereby full time is defined as at least 20 hours a week until 1978, 15 hours between 1979 and 1987, and 18 hours from 1988.

III.2 German Trends in Wage Inequality and Job Polarisation

Prior to discussing regional distinctions of job polarisation and wage inequality, I will first discuss general trends in Germany. Figure 1 plots the indexed wage growth for the 85th, 50th, and 15th percentile of the wage distribution. The evolution of wage can be segregated into two periods: Harmonised wage growth until the mid-1990s, and diverging wage growth thenafter (see also Card et al. (2013); Dustmann et al. (2009)).

< Include Fig. 1 about here >

Wages grow in parallel until the mid-1990s. With the exception of an episodic strong wage increase at the upper tail between 1983 and 1984, wages stagnate in the early 1980s and start to grow from the mid-1980s until the early 1990s. The immediate post-unification era is then characterised by steady wages. Wage dispersion starts from the mid-1990s. Wages at the top and bottom diverge. Bottom wages first decline slowly and plummet from 2003. The strong decline of bottom wages only cease in 2008. Wages at the middle slightly grew from the mid-1990s to 2003, followed by a slight decline. Top wages constantly increased from 1995 to 2003 and stagnated thenafter.

These wage trends can be directly transferred to changes in wage inequality that is displayed in figure 2. Prior to the mid-1990s, the rise in total wage inequality can be fully attributed to upper tail wage inequality, more specifically the episodic ascent in upper tail wages between 1983 and 1984. From the mid-1980s to the mid-1990s, wage inequality is unchanged. Between 1995 and 2008, wage inequality started to continuously grow at both tails. Thereby, the rise in lower wage inequality outpaces the rise in upper tail wage inequality.

< Include Fig. 2 about here >

The pattern of employment growth varies depending from whether the wage distribution is sorted according to mean wages or mean skills. Average wages are not neccessarily increasing with average skills, especially for occupations at the bottom of the wage distribution. Generally, job polarisation in Germany rather follows a j-form rather than a typical u-form (Dustmann et al., 2009). Figure 3 illustrates smoothed occupational growth between 1980 and 2010 by 1980 wage percentiles and skill percentiles. Regarding wage percentiles, gains are highest at the top of the wage distribution and lowest around the 60th percentile. A second mode emerges around the 30th percentile. Occupational growth is negative at the very bottom. The pattern does not clearly indicate a j-form. It rather reflects an s-form. Still, partitioning the distribution in tertiles as in Acemoğlu and Autor (2011), upper and lower tail's rise in employment shares outstand the decline in the middle of the distribution. Ordering the distribution according to average skills result in a clear j-form of employment growth. There is a mode at the top and bottom. Occupational shares in the middle decline.

< Include Fig. 3 about here >

III.3 Regional Polarisation

This study takes a advantage of regions that differ in their extent of job polarisation. These regions are 204 local labour markets (LLM henceforth) in (West) Germany. These LLM are defined by commuting patterns (Kropp and Schwengler, 2011). In this manner, they represent local economies and labour markets better than county boundaries. They resemble U.S. Commuting Zones that were employed to analyse regional employment polarisation among others by Autor and Dorn (2013).

Shifts in employment demand and the adoption of technological change varies regionally. This study follows the exploration by Dauth (2014) to distinguish regional job polarisation. Dauth (2014) analyses regional polarisation in Germany accounting for regionally varying employment shifts. He thereby follows the implementation by Goos and Manning (2007), who introduced the term job polarisation. By that, occupations are ranked according to mean wages in an initial year. Employment growth by the rank of occupation is then computed over time. An OLS regression of occupational growth with the rank and squared rank as explanatory variable is then run. The squared term gathers the u-shaped pattern of occupational growth, i.e. growing employment shares at both tails of the wage distribution relative the middle.

Dauth (2014) follows this method for German data. He estimates occupational growth from 1980 to 2010 by the rank and squared ranked of occupations – sorted according to 1980 mean wages. For Germany, he estimates (t-values in brackets):

$$\%\widehat{Emp}_{1980-2010} = -11.118 - \underset{(-3.5)}{.605}\, rank_{1980} + \underset{(4.76)}{.003} rank^2_{1980}. \tag{1}$$

Dauth (2014) repeats this estimation for all LLM and explores the squared parameter that determines the u-shape of occupational growth to operationalise the regional degree of job polarisation. He then categorises regional labour markets with differing patterns of occupational change:

1. negative job polarisation: a negative t-ratio (6 LLM, 1.2 % of the workforce),
2. weak job polarisation: a t-ratio between zero and the 5 %-significance level (54 LLM, 10.4 % of the workforce),
3. job polarisation: a t-ratio between the 5 %-significance level and the t-ratio estimated for Germany (124 LLM, 55.4 % of the workforce),

4. strong job polarisation: a t-ratio above the t-ratio estimated for Germany (20 LLM, 33.1 % of the workforce).

Job polarisation occurs in the majority of local labour markets, where the majority of the workforce is concentrated. Figure A1 in the appendix displays a map of (West) Germany and its LLM with different degrees of job polarisation. Significant employment polarisation occurs in 144 out of 204 LLM that represent 88 % of the workforce. German employment polarisation is significant, since it is driven by the majority of the workforce that is employed in regions, where employment polarisation occurs. Nonetheless, job polarisation is not omnipresent. The fraction of the workforce in LLM that are not affected by job polarisation only represent 60 LLM, with nothing but 12 % of the total German workforce. Out of these, 6 LLM or 1 % of the workforce experience a negative job polarisation. Only one region is negatively polarised at the 5 % level of significance.

Figure 5 depicts the different patterns of employment polarisation for each type of region. It plots job growth between 1980 and 2010 for each percentile according to 1980 wages by occupation.[1] The size of the circles denote the number of occupations in 1980. The dashed line represents the estimated occupational growth applying a weighted OLS regression with percentile and squared percentile as explanatory variable.

< Include Fig. 5 about here >

Fitted occupational growth is negative at both tails in negatively polarised LLM, which leads to an inverse u-shape of occupational growth. Weakly polarised local labour markets are characterised by a near-monotone occupational growth. Fitted employment growth is positive at the top, and negative occupational growth at the bottom. Fitted occupational growth is positive at both tails in polarised and strongly polarised LLM. The curvature of the u is larger in strongly polarised LLM.

The initial share of high-skilled employment is relevant to the adoption of new technologies that finally leads to employment polarisation (Accetturo et al., 2014; Beaudry et al., 2010; Marinelli, 2013). German data confirm this finding: Figure 4 plots regional employment shares by skills.[2] There is an educational sorting of regions with respect to higher education. Throughout the whole observation period, the employment share of workers with higher education is larger the more a region is subject to job polarisation.

< Include Fig. 4 about here >

Disparities in high-skilled employment shares rise over time in German regions. The adoption of new technologies, that is triggered by an initial higher share in higher education, is self-amplyfing and regional human capital differentials increase over time (Consoli et al., 2013;

[1]Due to data restriction, I use percentiles instead of the rank of the job to increase the number of observations.

[2]Low education is defined as having not completed vocational training, medium education as having completed a vocational training, and high education as having completed a university degree.

Marinelli, 2013). Differences in higher education between negatively and weakly polarised LLM barely exist. Both types of regions do not experience significant job polarisation. Due to this similarity, they will be pooled in some parts of the following analyis.

Low- and medium-skilled employment shares seem not to be relevenant for employment polarisation. Low-skill employment shares are similar across regions. Only negatively polarised LLM hold a diverse low-skilled employment share that converges to the remaining regions. The evolution of medium-skilled employment shares is distinct, but do not follow a clear pattern.

IV What is the Link between Job Polarisation and Wage Inequality?

IV.1 Regions as the Identification Strategy of Job Polarisation

Cross-country as well as within-country analyses on the link between the employment and wages structure should be considered with care when drawing a link between the two. Cross-country analyses capture variation in occupational and wage shifts between countries (Goos et al., 2009). Within-country analyses typically compare the wage structure before and after the emergence of job polarisation (Autor et al., 2008). Difficulties arise from a possible variation between countries or between different time periods in (1) the supply of skills, the (2) adaptation of new technologies resulting in varying demand for skills, and (3) the institutional framework – influencing the formation of the wage structure, notably at the bottom end.

First, the growth rate of higher education has a crucial impact upon wage inequality. Wage inequality increases when technological change outpaces educational expansion, and shrinks when educational expansion outpaces technological change (Tinbergen, 1975). This argument is incorporated in Katz and Murphy (1992), who explain the increase in wage inequality in the U.S. by a relative shortfall in educational expansion from the 1970s. In contrast, Beaudry and Green (2003) find a balanced path of human capital accumulation in Germany as explanatory for its wage stability in contrast to the U.S. Abraham and Houseman (1995) further describe how the constantly growing supply of higher education in Germany, that fell short in the U.S., explains its stability of the wage structure.

Second, differences also appear to the implementation of technological change. Expenditure on Research and Development is largely higher in the U.S. than in European countries. Gross domestic expenditure on R & D as percentage of GDP is 2.79 in the U.S., as compared to an OECD average of 2.4, and only yielding 1.97 in EU28 countries in 2012 (OECD, 2014). Similarly, the role of Information and Communication Technology is more pronounced in the U.S.: The share of ICT value added in business sector value added in the U.S. amounts to 7.1 % as compared to an OECD average of 6.0 %. Crescenzi et al. (2007) further find differences in the dynamics of innovation in the U.S. and Europe, whereas the European innovation system lags behind. Lastly, U.S. individuals are more optimistic about new technologies, rendering U.S. workers more open to adopt innovative technologies Gaskell et al. (2005). This variety may cause differing demand in high-skilled workers.

Third, institions vary between countries. Blau and Kahn (2002) find that technological change results in a rise in wage inequality in the U.S., while increasing unemployment among the low-educated in Europe due to rigid wage setting. In a comparative analysis on the impact on innovation on wage inequality, Lee and Rodríguez-Pose (2013) find divergent trends between the U.S. and European cities. Innovation triggers job polarisation both in the U.S. and Europe. While job polarisation mitigates inequality through higher wages for low-skilled workers in the U.S., it increases inequality in Continental Europe since polarisation entices low-skilled workers into the labour market. Low-wage workers are likely to be already in employment in the U.S. and are not pulled into the labour market, since the U.S. welfare state is less benevolent than their Continental European counterparts OECD (2015).

These issues render cross-country as well as within-country analyses difficult to assess the impact of job polarisation upon wage inequality. It is difficult to distinguish whether wage inequality is higher in one country than another due to differences in the institutional framework, supply and demand of high-skilled workers, or the degree to which it is affected by job polarisation. Likewise, it renders within-country analyses between two points in time difficult. It is unclear whether a rise in wage inequality occurs due to shifts in the institutional framework, a shortfall in the supply of high-skilled labour or increasing demand due to increasing innovation, or lastly occupational shifts. By contrast, within-country analyses and the co-existence of polarised and non-polarised regions within a country render it possible to adress the question of how job polaristion shapes the wage distribution. Most importantly, other influencing factors, that also determine the wage structure, can be held constant.

I use regional variation in job polarisation to overcome these issues. Institutional factors, such as employment law, union coverage, or social preferences to wage compression can be assumed alike between regions of one country. Supply of high-skilled labour, arguably a main trigger of the implemention of technological innovation is harmonised within a country. Further, curricula and the definition of educational levels do hardly vary within a country. Although universities may be more present in cities than in rural areas, within-country migration can compensate these differentials due to free movement of workers, non-existing language barriers, and rather small geographic distances between polarised and non-polarised LLM (see also figure A1). Lastly, access to technology can be assumed alike within a country.

IV.2 Regional Trends in Wage inequality

First and foremost, the rise in wage inequality occurs universally in Germany no matter the degree of regional job polarisation, but it differs in magnitude. Figure 6 illustrates wage inequality for each type of region over time. The upper-left panel describes the evolution of total wage inequality. In all regions, total wage inequality remains hardly unchanged up until the mid-1990s, and accelerates subsequently until 2008, whereupon it stagnates. The rise in total wage inequality is both fuelled by upper and lower wage inequality. While upper tail inequality steadily grows, lower inequality expands abruptly from the mid-1990s. These patterns largely correspond to the development that were described for Germany in section III.2.

< Include Fig. 6 about here >

Although the patterns of the rise in wage inequality resemble between regions, there are some distinctions. In 1980, strongly polarised LLM are most equal. In 2010, these LLM were most unequal. Similarly, negatively polarised LLM are most unequal in 1980, while they are second-most equal in 2010. This hints at a possible relationship between job polarisation and wage inequality. Clearly, in 2010, when technological change reshaped the wage structure, strongly polarised and polarised LLM are more unequal than LLMs that were not affected by job polarisation.

What drives this divergence? The divergence in wage inequality is mostly due to differences in lower inequality. Relative gaps in upper inequality are mostly constant. The higher the degree of job polarisation the higher is upper inequality. This excludes the rapid ascent in upper inequality from 1983 to 1984, which is larger in polarised LLM. Other than that, developments in upper inequality are harmonised and relative gaps remain unchanged over time.

Differentials in lower inequality are larger. In 1980, differences are broad, while strongly polarised LLM are distinctly more equal than negatively and weakly polarised LLM. The period until the mid-1990s is characterised as an adjustment of lower inequality and disappearance of regional differences – while lower inequality of the whole country remains constant (see figure 2). While lower wage inequality strongly declined in negatively and weakly polarised LLM, it only slightly fell for polarised LLM, and remained stable for strongly polarised LLM. This period can be characterised as a harmonisation in lower inequality between regions – since there are no regional differences by the mid-1990s. It also implicitely speaks in favour of a stiff wage setting, and workers opting out of the labour market when wages do not yield comparative wages.

Lower inequality abruptly rises from the mid-1990s in all regions. The extent of the rise in lower inequality differs regionally. The higher a region is polarised, the larger is the rise in lower inequality. Still, given the very parallel movements, relative small inequality gaps between regions, and the abrupt rise, it seems unlikely that market forces stemming from occupational changes trigger the rise in lower inequality. By contrast, it could stem from a deunionisation process and flexibilisation of wages that occured in this era and mostly affect bottom wages (Dustmann et al., 2009, 2014).

Understanding the development of wages at different points of the wage distribution is essential to understand what drives the gaps in inequality. Figure 7 plots relative wage gaps for each region relative to the whole workforce in Germany over time. Throughout the whole sample period, there is a clear ordering of wages regarding the degree of polarisation. Wages are highest in strongly polarised LLM, and lowest in negatively polarised LLM. Wages in strongly polarised LLM are constantly highest and above the sample mean – this is similar to findings in the UK, where polarised cities reach the highest wages at all points of the wage distribution (Lee et al., 2013).

< Include Fig. 7 about here >

The upper left panel illustrates the wage gap at the 15th percentile for each region relative to the whole sample. The wage gap in strongly polarised and polarised LLM are constant over the years. By contrast, the relative wage gap in weakly and negatively polarised LLM catch up until the mid-1990s, and remain constant thenafter. The adjustment process prior to the mid-1990s was larger in negatively polarised LLM than in weakly polarised LLM. This adjustment process also hints at institutional framework contracting relative regional wage gaps at the lower tail.

Wage gaps at the median of the wage distribution are overall constant. Relative wage gaps in strongly polarised LLM slowly and constantly rise throughout the years, while they slightly but constantly fall in polarised LLM. Weakly polarised LLM experienced constant wage gaps until the mid-1990s and a decline thenafter. The relative wage gap narrows in negatively polarised LLM until the mid-1990s and falls in parallel to weakly polarised LLM thenafter. In all, the comparably stark increase in strongly polarised LLM's lower tail inequality can be attributed to a larger rise in median wages as compared to wages to the 15th percentile. At the same time, the growing distance in the relative wage gaps at the median is more prounounced than at the lower tail in weakly and negatively polarised LLM – explaining why the increase in lower inequality is smaller in these regions than in strongly polarised LLM.

At the 85th percentile, relative wage gaps steadily rise in strongly polarised LLM and fall for the remaining regions. The fall in the relative wage gap in polarised LLM is minor to weakly and negatively polarised LLM, whose wages are similar. Bearing in mind the very similar development in the wage gap at the median, this explains why differences in upper inequality are comparably constant over time.

Regional wage differentials are comparably constant, in contrast to the very strong rise in wage inequality. It points at rising wage inequality as a universal phenomenon, and a low impact of employment shifts onto the wage structure, since relative wage gaps are constant and, in contrast to lower inequality, do not rise abruptly. The decline in wages at the bottom (see also figure 2) thus is universal and may be attributed to a universal loosening of institutional frameworks (Dustmann et al., 2009).

IV.3 Distributional Decomposition Method

Shifts in wage inequality are shifts in wages at different points of the wage distribution. This may occur mechanically. The share of high-skilled workers and top-paying occupations constantly increased in the past three decades. Assume wages being unchanged within occupations and a constant return to higher education, upper as well as total wage inequality must mechanical shift upwards due to a numerical rise in the share of high-skilled workers and top-paying occupations. This mechanical shift is referred to as composition effect (Firpo et al., 2009). The wage structure may also reshape structurally, i.e. due to shifts in wages within occupations, the return to education, etc. For example, the increasing demand for high-skilled workers in top-paying occupations can create a shortfall, which is follow by increasing wages in these occupations and increasing returns to education. This study aims at explaining how job polarisation shapes the wage structure structurally, i.e. how the wage structure reshapes if one accounts for the changing composition of the workforce such as occupations and skills.

I apply distributional decomposition methods to disentangle the structural from the composition effect. More specifically, the approach introduced by DiNardo et al. (1996) is applied. They evolved this method to analyse the impact of institutional and labour market factors upon the wage structure in the U.S. The analytic framework grounds upon the seminal work by Oaxaca (1973). The latter decomposition is based on the question, what a worker with certain characterics would earn in one group, e.g. a certain year, region, etc., had she worked in another group, e.g. another year, region, etc. It thus divides observed wage differentials between two groups into an explained component (composition effect) and unexplained component (structural effect). The explained component refers to differences in the composition of the workforce, such as education, experience, etc. The unexplained component or structural effect corresponds to the remaining wage differentials.

While the method established by Oaxaca (1973) only decomposes differentials at the mean, the method suggested by DiNardo et al. (1996) goes beyond the mean. The suggested distributional decomposition method is capable of capturing composition and wage structure effects along the wage distribution. It represents an appropriate means to analyse the wage structure and wage inequality. This method has been among others been applied in Autor and Dorn (2013) and Dustmann et al. (2009) to analyse the impact of occupational changes onto the wage structure.

The idea behind this distributional decomposition is to replace the distribution of characteristics of the workforce X of one group A, $F_{X_A}(X)$, with the distribution of X of the other group B, $F_{X_B}(X)$. The counterfactual wage distribution $F_{Y_A^c}(y)$ is the distribution of wages in group B, had they been paid like workers in group A. It is computed using a reweighting factor of the following form:

$$F_{Y_A^c}(y) = \int F_{Y_A|X_A}(y|X)\Psi(X)dF_{X_A}(X), \tag{2}$$

where

$$\Psi(X) = \frac{dF_{X_B}X}{dF_{X_A}X} \tag{3}$$

is the reweighting factor. The reweighting factor is computed by pooling both groups and estimating a probit for the probability of belonging to group B as a function of the characteristics of the workforce X. The reweighting factor is:

$$\Psi(X) = \frac{Pr(X|D_B = 1)}{Pr(X|D_B = 0)} = \frac{\frac{Pr(D_B=1|X)}{Pr(D_B=1)}}{\frac{Pr(D_B=0|X)}{Pr(D_B=0)}}. \tag{4}$$

The observed differentials in the wage structure is decomposed into an explained composition effect, and unexplained wage structure effect. The observed differential is the sum of explained and unexplained effect. The composition effect then is the difference between the counterfactual density function and the density function for group A.

$$\Delta_X^{f(y)} = f_{Y_A^c}(y) - f_{Y_A}(y). \tag{5}$$

Observed differentials between two groups in total wage inequality, which here is defined as the 85th-15th percentile wage differential, is the difference between the wage difference at the upper tail between both groups, and the difference at the lower tail:

$$\Delta_X^{85-15} = [Q_{A,.85} - Q_{B,.85}] - [Q_{A,.15} - Q_{B,.15}], \tag{6}$$

and the composition effect of total wage inequality is the difference between the wage differentials at the upper tail between the counterfactual and actual group, and the same difference at the lower tail:

$$\Delta_X^{85-15^c} = [Q^c_{A,.85} - Q_{A,.85}] - [Q^c_{A,.15} - Q_{A,.15}]. \tag{7}$$

The wage structure effect is the subtraction of the composition effect (equation 5) from the observed total wage inequality (equation 7).

IV.4 Decomposing Differentials in Wage Inequality between Non-Polarised and Polarised LLM

The following analysis conducts the aforementioned decomposition method adressing what a worker with certain characterics in a region that is not subject to employment polarisation would have earned, had she worked with the same characteristics in a region subject to job polarisation. Negatively and weakly polarised LLM are pooled into one group (denoted 'non-polarised' henceforth), where job polarisation did not occur, and polarised and strongly polarised LLM are pooled into another group (denoted 'polarised' henceforth), where job polarisation did occur. This approach guarantees a clear-cut status quo. The probability of working in a polarised regions is conducted using a probit function using dummy variables for 5 educational dummies, and interaction terms thereof with potential experience and squared potential experience. Dummy variables for occupations are further included.

First, wage differentials are observed in 1980, before the event of job polarisation, and second, in 2010, when job polarisation has occured. The wage wage differentials and differences in wage inequality are then analysed and decomposed in order to asses the impact of job polarisation upon wages and wage inequality.

Table 1 displays wage differentials between both groups in 1980, as well as its decomposition in composition and structural effects. The observed differences are universally positive, meaning observed wages are higher in polarised than in non-polarised LLM (see also figure 7). The observed wage gap is roughly 13 % at both tails, and 10 % at the median. The differing composition of the workforce explains about half of the wage gap.

$<$ Include Tab. 1 about here $>$

These wage gaps are directly reflected by the differences in wage inequality. Total wage inequality is identical in polarised and non-polarised LLM in 1980. This occurs since observed upper inequality that is higher in polarised LLM (+3.2 %) is levelled off by smaller lower tail inequality (-3.3 %). Similarly, the composition of the workforce, that would suggest higher total wage inequality in polarised LLM (1.7 %) is levelled off by a structural wage effect reducing wage inequality (-1.9 %). While composition and structural effect offset one another regarding total wage inequality, they add on one another regarding upper and lower inequality. In sum, structural wage inequality differentials are comparably low as compared to larger differentials in wages at the observed points of the wage distribution.

Table 2 illustrates the same differentials in 2010. Observed wage differentials ascent prounouncedly at the top, and moderately at the median, while they shrink at the bottom. The relative wage gap is now highest at the top of the wage distribution, and lowest at the bottom. Wages at the top diverge, converge at the bottom and are constant at the median – which has also been described in figure 7. Observed wage differentials are similarly equally split between the composition and wage structure effect at the top and median. The observed wage gap is mainly compositionally at the bottom. The composition effect is positive at the top and median, and negative at the bottom.

< Include Tab. 2 about here >

Differentials in wage inequality rise – both regarding upper and lower inequality. Total wage inequality, identical in 1980, now amounts to 13 %. Though these differentials seem fuelled by differentials in upper tail wage inequality (11 %) at first sight, it should be born in mind that upper and lower inequality rise homogenously by 7.6 and 5.9 percentage points. Differences in the workforce composition gain weight in explaining differences in wage inequality. The structural difference in total wage inequality is small. As in 1980, structural differentials in upper and lower inequality level off one another. Structural differences in lower inequality are considerably unchanged and still negative. Though structural upper inequality rises, this is due to noticeable relative growth in structural differentials of upper tail wages.

How to interpret these findings? In order to do so, it is necessary to analyse the growth in the relative wage and wage inequality gap over time, which are displayed in table 3. Polarised LLM are characterised with higher wage growth at the top and median, while the relative bottom wage gaps fall. Shifts in the composition of the workforce explain a main part of the rise at the top and median, as well as the fall at the bottom. Notwithstanding, wage gaps increase structurally at all points of the wage distribution and notably at the top.

< Include Tab. 3 about here >

The relative rise in total wage inequality is equally split by a rise in upper and lower inequality. The workforce composition can account for the major part of the relative increase. The rise in structural inequality is small and limited to upper tail inequality. The latter can be mainly explained by structural wage growth at the top of the wage distribution. Polarised LLM, characterised by comparably small inequality in 1980, and higher relative lower inequality in

2010 (see figure 7), shifted their workforce composition – structural shifts in lower inequality do almost not occur. At the same time, the shift in structural upper inequality accounts for the rising structural gap in upper tail wages.

The presented result indicate that job polarisation only barely reshape the wage structure – the main shifts occur to upper tail wages and the upper tail wage inequality. By contrast, it could be clearly demonstrated that the relative wage gaps rise through the years, positively affecting wages in regions where job polarisation occurs. The relative increase in wage inequality in polarised regions occurs mainly through composition effects.

Are these results robust? Tables B2, B2, and B3 in the appendix illustrate the same approach but distinguishing between polarised and strongly polarised LLM. The main results remain unchanged. Magnitudes vary. Wages and wage growth are higher in strongly polarised regions. Strongly polarised labour markets, being structurally more equal in 1980, experience a larger rise in wage inequality than polarised labour markets. Again, this can be mainly attributed to compostion effects. Roughly 80 % of the rise in observed wage inequality can be associated to differences in the workforce. It remains a slightly larger rise in structural wage inequality. Notwithstanding, strongly polarised labour markets are structurally more equal than polarised labour markets. This holds both for upper and lower inequality.

IV.5 The link between occupational and wage growth

Results from the decomposition of the wage structure hint at a low link between job polarisation and wage inequality. The channels of wage growth, due to the interaction of supply and demand, or skill shifts within occupations, are further inconclusive. An alternative approach to assess the link between occupational and wage shifts is to analyse their correlation. This approach directly follows Autor et al. (2008) and has also been implemented in Dustmann et al. (2009) for the German labour market, and in Coelli and Borland (2015) for the Australian labour market. Autor et al. (2008) implement an OLS regression that assesses the relationship between shifts in employment shares and wage growth by wage percentile:

$$\Delta E_{p,t} = \alpha_t + \beta_t \Delta w_{p,t} + \epsilon_{p,t} \tag{8}$$

In this equation, $\Delta E_{p,t}$ denotes the percentage employment change, and $\Delta w_{p,t}$ denotes the percentage employment change, at wage percentile p and over time t. Employment change is therein measured by the change of the employment share. Wage growth is measured as the change in relative mean wages at each percentile over time. For Germany, Dustmann et al. (2009) find a positive relationship estimating solely above the median, but no correlation below the median.

I will perform a similar analysis, though not only subdividing the data above and below the median, but also distinguishing between regions subject to different degrees of job polarisation. In order to increase the number of observations, negatively and weakly polarised LLM are pooled.

Table 4 illustrates regression results for various regions, periods, and segments of the wage distribution. Scatter plots of the relationship are displayed in figure A2 in the appendix. There is a positive and significant relationship for the whole sample and above the median similar to Dustmann et al. (2009). The positive and significant relationship for the whole sample seems spurred by a firm link above the median, while the relationship is null below the median. Segmenting the estimation in decades, results for the whole observation period appear to be fuelled by a strong link in the 1980s. The remaining estimations only yield insignificant coefficients. Explanatory power is overall low, with the exception of the 1980s and above the median.

< Include Tab. 4 about here >

The correlation patterns alter when studying each region seperately: Besides a positive correlation above the mean in the 1980s, all coefficients are insignificant for weakly and negatively polarised LLM. Similarly, in polarised LLM, there is only a positive significant correlation for the 1980s, that is driven by a positive correlation above the median.

Interestingly, the pattern differs for strongly polarised labour markets. For the whole sample period, there is a positive and significant correlation between employment and wage growth. There is a positive correlation for each decade individually, although this is mainly due to a strong correlation above the median. Only in the 2000s, there is a significant and positive correlation below the median. Further, the coefficient, though not significant, below the median is always positive in strongly polarised LLM in each decade, while it is negative in the remaining LLM.

Overall, the link between occupational and wage growth is inconclusive: There are hints of rising wages with rising employment shares at the top, but not so at the bottom of the wage distribution. These results are further limited to the 1980s. These results are difficult to reconcile with a direct link between employment and wage growth. Strongly polarised LLM are peculiar: First, all coefficients are positive. Second, there are significant coefficients outside the 1980s. Third, there are significant coefficients below the median, both in the 1980s and 2000s as well as for the whole observation period.

From this perspective, a possible shortfall in the supply of skilled labour, if existent, seems limited to the 1980s. At the same time, an erosion of wages at the bottom due to displaced workers in medium-paying positions seems unlikely: The correlation between employment and wage growth below the median is not significant, except for strongly polarised LLM, where the fall in employment shares is most pronounced. Only in strongly polarised LLM, the link is positive and significant. The results hint at within-occupation shifts in skills due to occupational upskilling. In order to acount for initial skills and upskilling, equation 8 is expanded:

$$\Delta E_{p,t} = \alpha_t + \beta_t \Delta w_{p,t} + \gamma_t \Delta s_{p,t} + \delta_t educ_t + \epsilon_{p,t} \tag{9}$$

In this equation, $\Delta s_{p,t}$ denotes the skill change by percentile, measured by the change of mean years of education, and $educ_t$ denotes the initial mean years of education at the beginning of the period by percentile. Within-occupation shifts in skills as well as the initial skills within occupations are captured in this equation. Further, the link between occupational and wage growth can be estimated independently from the skills within occupation and occupational skill shifts.

Table 5 displays regression results for the whole sample and full period, various regions, above and below the median and each decade. Regression results are very distinct from table 4. First, explanatory power has increased markedly. Second, the coefficient for initial education is positive, and in most cases very strongly significant. Third, changes of skills within occupation play a major role in occupational growth. The correlation is positive and in most cases strongly significant – except for the 2000s. Fourth, the correlation between wage and occupational growth changes sign – it is negative for all regions, segments and decades. Significance is mostly limited to the 1990s and below the median. Accounting for skills entirely changes regression results – thereby strongly improving explanatory power of the regression.

$<$ Include Tab. 5 about here $>$

Regional subsample estimations are similar and resemble estimations for the full sample with minor exceptions. Estimating the link between occupational and wage shifts with and without the consideration of skills leads to contrasting results. The positive relationship between occupational and wage shifts in table 4 appears to spuriously explain differing skills and skill shifts. The coefficient becomes negative or insignificant after accounting for skills. At the same time explanatory power of the model rises firmly. The negative relationship reject a scenario of demand-driven wage shifts due to job polarisation.

These results oppose a positive relationship between occupational and wage shifts. At the same time, they highlight that technological change rises skill requirements within occupations. Regional differentials vanish although they vary in their employment growth pattern. As described in section III.3, these regions vary in the supply of high-skilled labour. In order to comprehend how job polarisation changes skill requirements, figure 8 plots these occupational shifts along the skill distribution, next to remaining components of equation 9.

$<$ Include Fig. 8 about here $>$

Occupational changes are near-monotonic for negatively and weakly polarised LLM, and represent a j-function for polarised and strongly polarised LLM. Despite variances in occupational shifts, wages shifts are near-monotonic in each region with positive wage growth above, negative wage growth, and zero wage growth at the median. The steepness of the monotonic function increases with the degree of job polarisation. Although occupational shifts vary, the pattern of wage shifts is identical. Interestingly, the intial occupational skill distribution is identical between regions. Before the event of job polarisation in 1980, skills within occupations are equivalent.

Diversity between regions appear with respect to the occupational skill shifts. In each region, change of skills represents a u-form, with higher skill growth at the top and bottom than at the middle. Until the 20th percentile, each region is identical in skill growth. Beyond the 20th percentile, skill growth is higher the more a region is subject to job polarisation. This rules out a scenario of supply driven wage shifts due to job polarisation. More specifically, it rules out a scenario, in which medium-skilled workers are displaced due to technological change and have to perform jobs at the bottom of the skill distribution. If such a scenario would hold, skill shifts at the bottom tail were larger in polarised than in non-polarised LLM. Likewise, an oversupply of high-skilled workers appear unlikely. Although skill shifts are larger in polarised LLM, they are directly translated in larger wage growth.

By contrast, the results point at increasing skill requirements the more a region is subject to job polarisation. Arguably, one may assume that technological change in polarised regions led to upskilling and higher skill growth in top-paying positions. The upskilling then leads to wage growth. A possible shortfall in the supply of high-skilled labour appear unlikely, since the relationship between wage and occupational growth is negative. High-skilled workers are attracted to polarised and more so by strongly polarised LLM (see figure 4). Migration likely compensates the relatively higher demand for high-skilled labour in polarised regions. At the same time, educational expansion seems to hold pace with increasing demand of high-skilled labour in Germany (Acemoğlu, 2003; Beaudry and Green, 2003; Katz and Autor, 1999).

V Conclusion

This paper contributes to the literature on the link between job polarisation and wage inequality. It contrasts the view that job polarisation is associated to rising wage inequality in the case of Germany, and thus conforms with Antonczyk et al. (2009); Beaudry and Green (2003); Dustmann et al. (2009); Freeman and Schettkat (2001). It further contributes to the literature stating distinct labour markets outcomes between Anglo-Saxon and Continental European countries, e.g. Acemoğlu and Autor (2011); Blau and Kahn (1996, 2002). It adds to the view that technological change and employment polarisation affect the wage structure differently in Germany than in the U.S. (Beaudry and Green, 2003; Lee et al., 2013). It lastly confirms a balanced growth path between the increasing demand for higher education and educational expansion in Germany (Abraham and Houseman, 1995; Acemoğlu, 2003; Beaudry and Green, 2003; Katz and Autor, 1999).

Technological change and job polarisation leads to increasing employment shares of top-paying positions and high-skilled workers in Germany. This mechanically drives up wage inequality, but does barely change the wage structure itself. Structural wage shifts in polarised regions relative to non-polarised regions are small and limited to wages at the top of the wage distribution. Regions, in which job polarisation occurs, do not differ in structural wage inequality to regions, in which job polarisation did not occur.

Moreover, employment shifts are not correlated to wage growth once accounting for skills. Employment growth is strongly positively correlated to initial skill levels and skill growth within jobs, but is not positively correlated to wage growth. Polarising regions face larger skill shifts within occupations, while they also attract a larger share of high-skilled workers. The concurrent increase in demand and supply levels off any impact upon wages.

Job polarisation thus is an unlikely driver of rising wage inequality in Germany. Bottom wage inequality, abruptly rising in the 1990s, can most likely be accounted to changes in the institutional framework (Dustmann et al., 2009). The constant rise in upper inequality can mainly be attributed to rising wages at the top, which is directly associated with skill shifts. Technological change appears to generally rise skill requirements within occupations in Germany. The growth path of supply and demand of skilled workers is constant and seems balanced, creating neither a shortfall nor an oversupply (Abraham and Houseman, 1995; Acemoğlu, 2003; Beaudry and Green, 2003).

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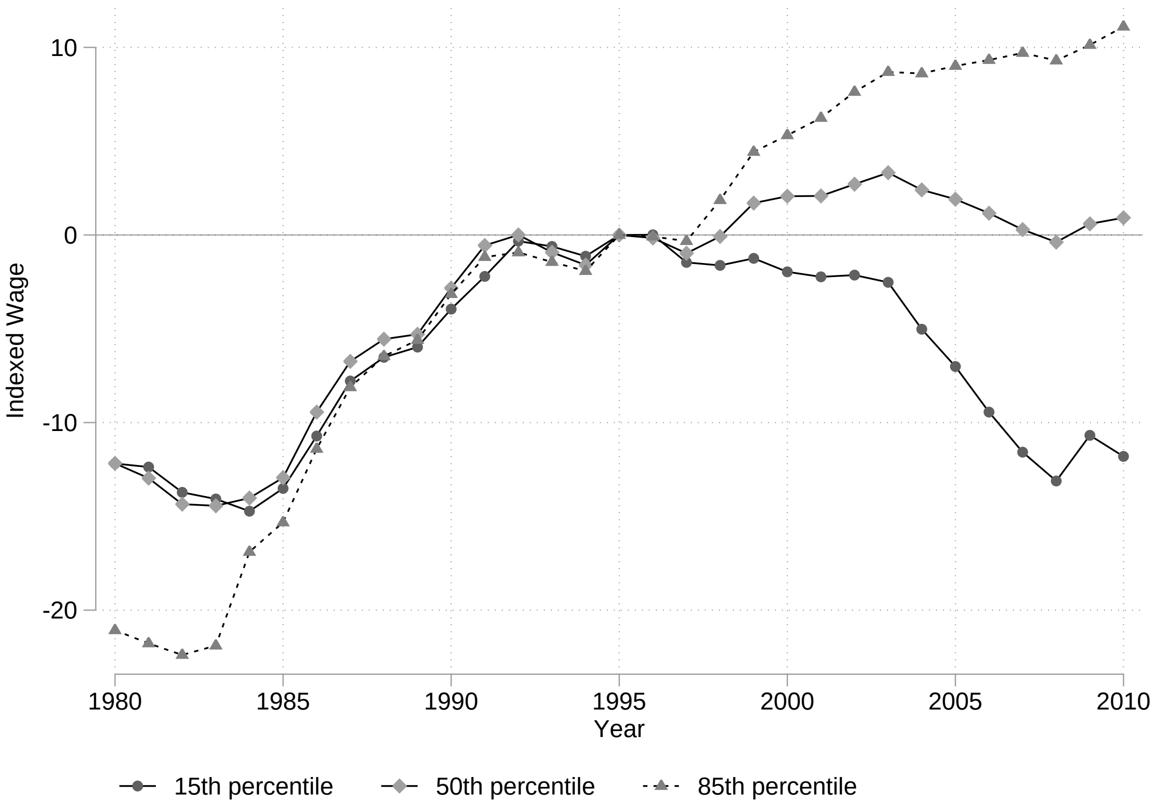
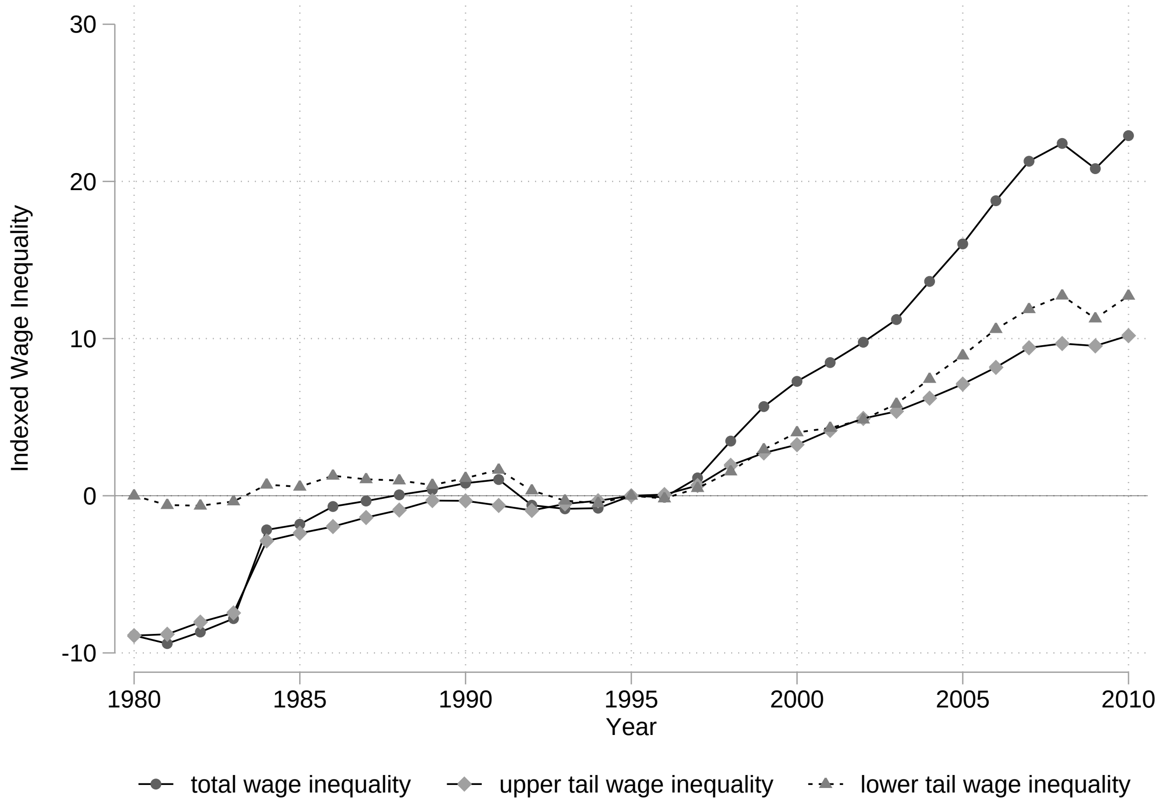
Figures

Figure 1: Indexed Wage Growth (1980-2010)



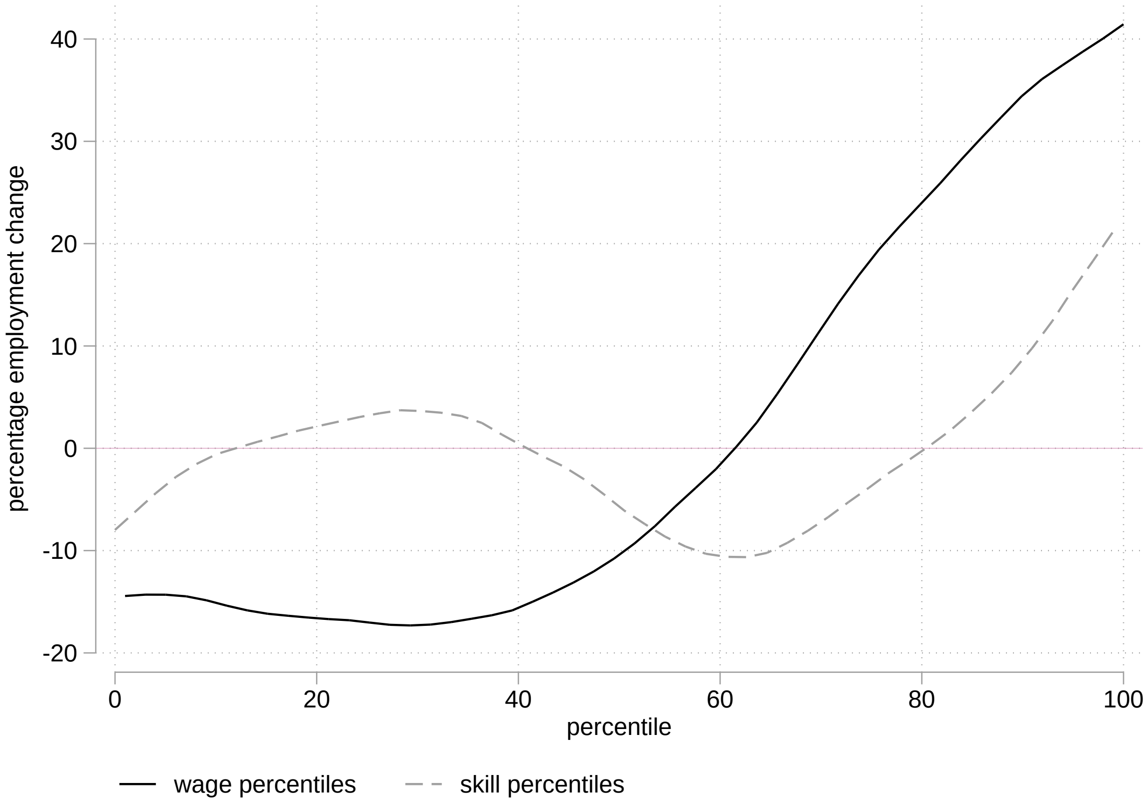
Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,888,775.

Figure 2: Indexed Wage Inequality (1980-2010)



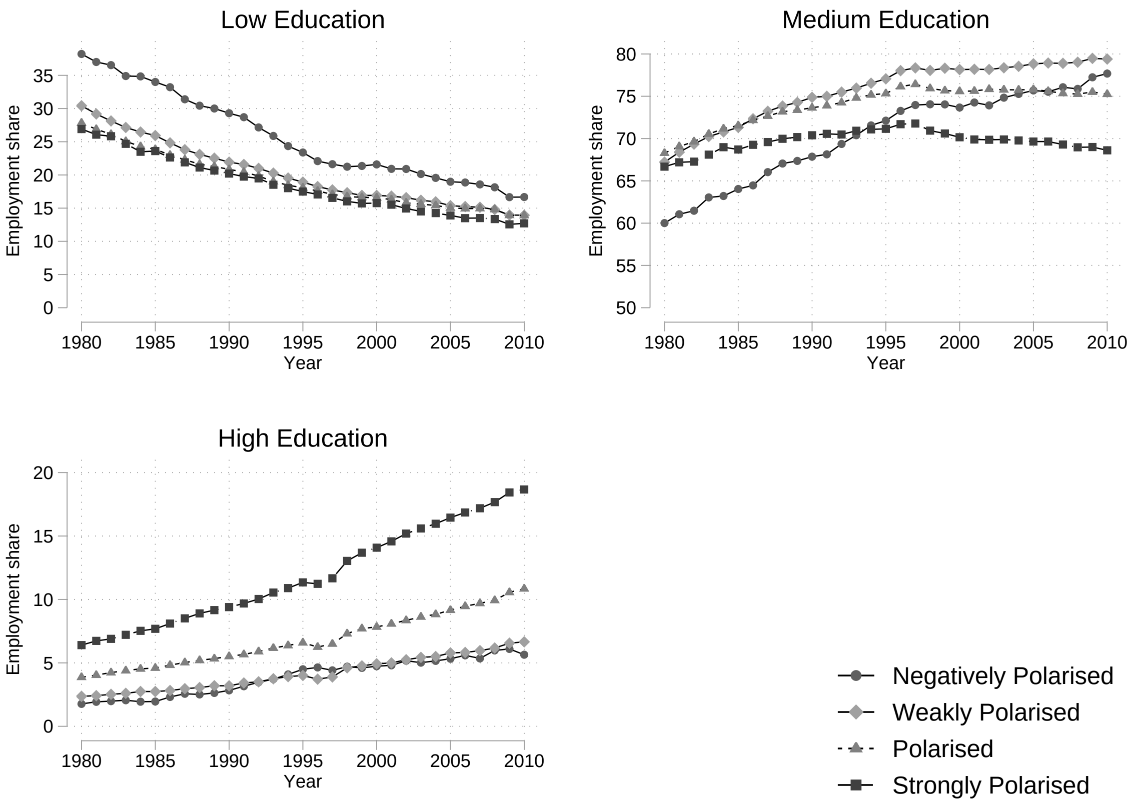
Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,888,775.

Figure 3: Occupational Growth – wage and skill percentiles (1980-2010)



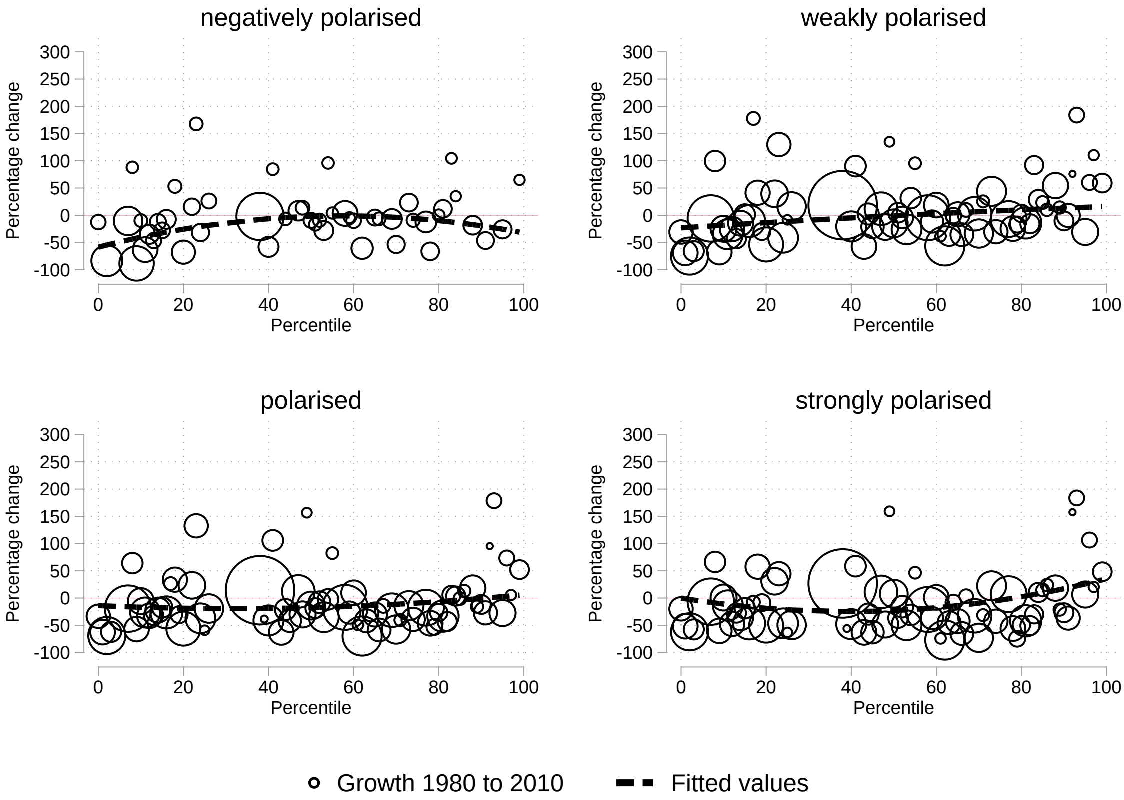
Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=305,996 in 1980, N=272,279 in 2010. Changes are smoothed using a local smoothing epanechnikov kernel function and a bandwith of 5.

Figure 4: Educational shares – by degree of job polarisation (1980-2010)



Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,898,110.

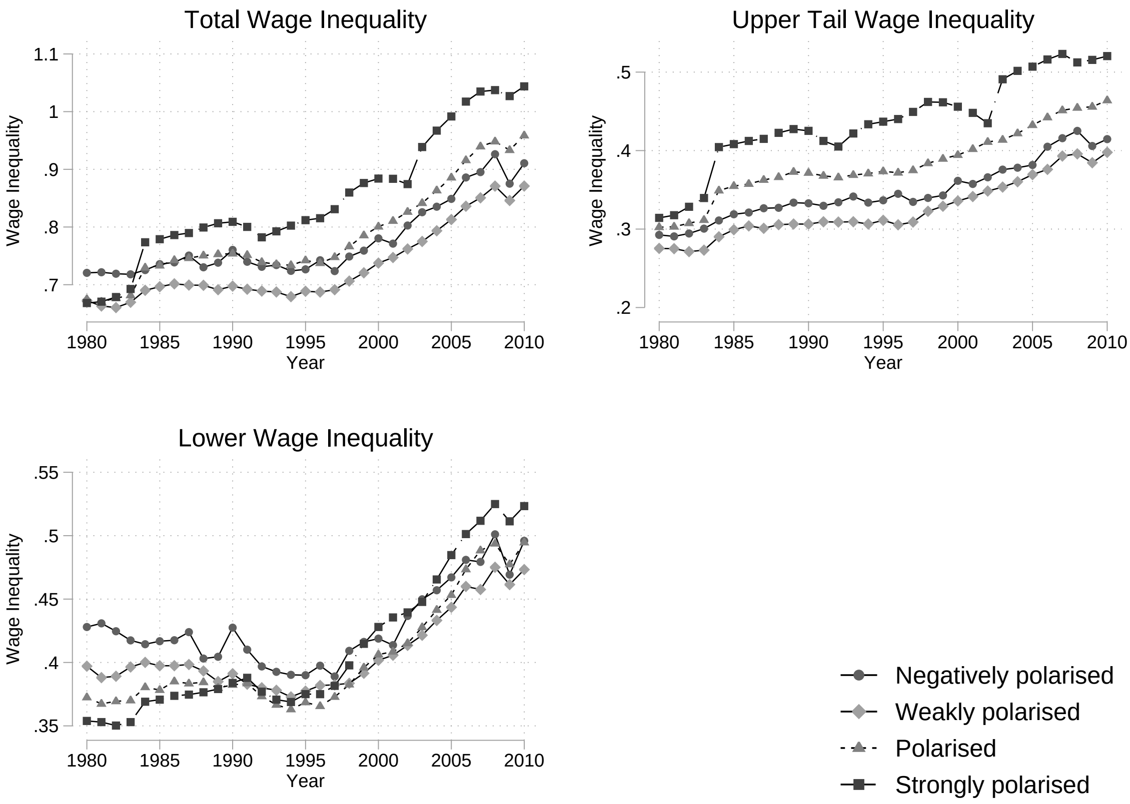
Figure 5: Fitted occupational Growth – by degree of job polarisation (1980-2010)



Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=577,829 Wage growth could not be computed due to data nondisclore in negatively polarised local labour markets for percentiles with less than 20 observations.

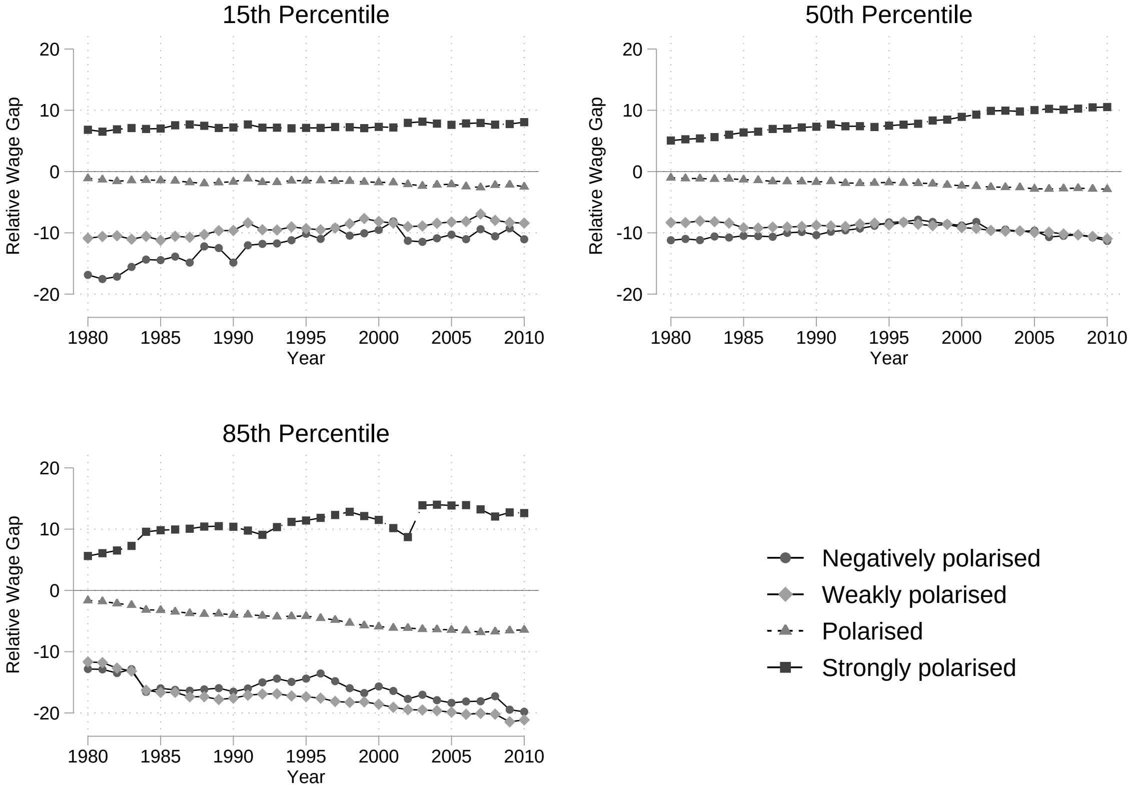
Observations are not displayed for percentage changes above 350% for the sake of visibility.

Figure 6: Wage Inequality – by Degree of Job Polarisation (1980-2010)



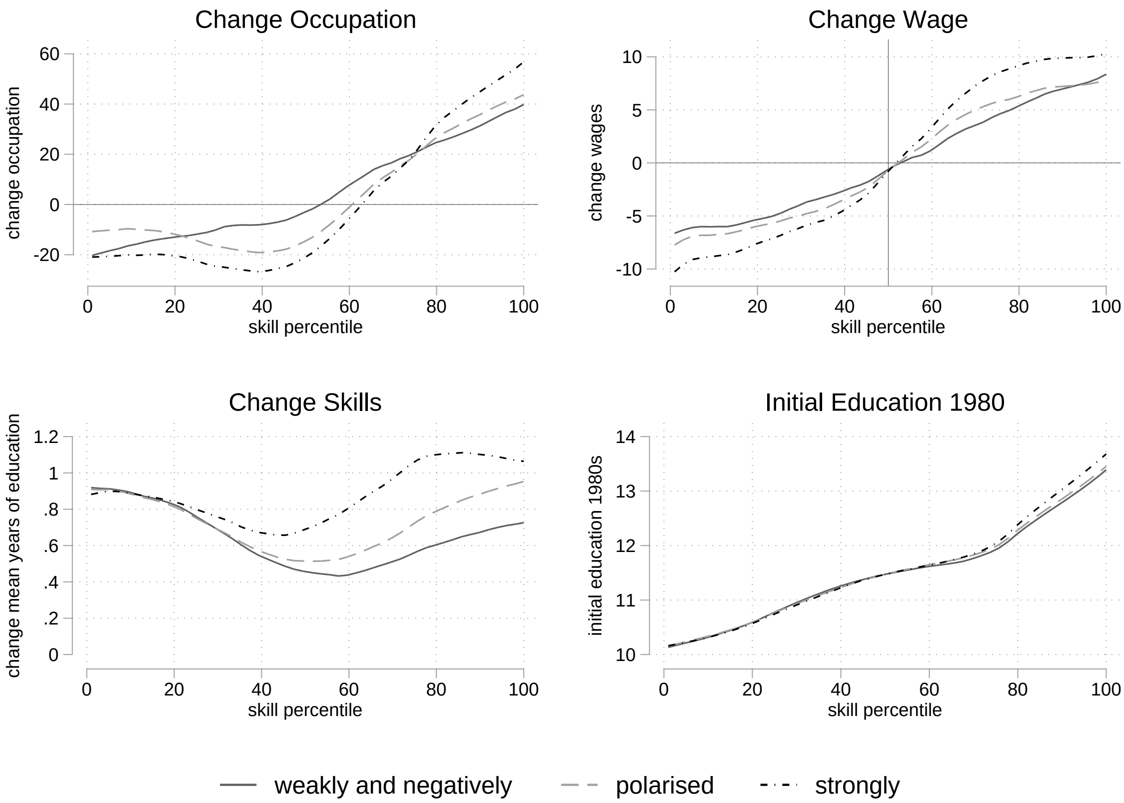
Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,886,214.

Figure 7: Relative Wage Gap – by Degree of Job Polarisation (1980-2010)



Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,886,214.

Figure 8: Occupational shifts, wage shifts, change of skills, and initial education by skill percentile – by Degree of Job Polarisation (1980-2010)



Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,886,214. Occupational growth is smoothed using a local smoothing epanechnikov kernel function and a bandwith of 10.

Tables

Table 1: Wage Gap in 1980: Quantile Decomposition – Reference Group: Polarised LLM

wage	difference	composition	structural
85th percentile	13.0%	6.7%	6.3%
50th percentile	9.8%	3.9%	5.9%
15th percentile	13.1%	5.0%	8.1%
inequality measure	difference	composition	structural
total wage inequality	-0.1%	1.7%	-1.9%
upper tail wage inequality	3.2%	2.8%	0.4%
lower tail wage inequality	-3.3%	-1.1%	-2.2%

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N= 306,455, N= 34,460 for non-polarised LLM and N= 271,995 for polarised LLM.

Table 2: Regional Wage Gap in 2010 – by Degree of Job Polarisation: Quantile Decomposition – Reference Group: Polarised LLM

wage	difference	composition	structural
85th percentile	23.4%	12.8%	10.7%
50th percentile	12.6%	5.3%	7.4%
15th percentile	10.1%	1.0%	9.1%
inequality measure	difference	composition	structural
total wage inequality	13.3%	11.8%	1.5%
upper tail wage inequality	10.8%	7.5%	3.3%
lower tail wage inequality	2.5%	4.3%	-1.8%

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N= 32,681, N= 241,041 for non-polarised LLM and N= 273,722 for polarised LLM.

Table 3: Regional Growth Wage Gap in 2010: Quantile Decomposition – Reference Group: Polarised LLM

wage	difference	composition	structural
85th percentile	10.4 pp	6.0 pp	4.4 pp
50th percentile	2.8 pp	1.3 pp	1.5 pp
15th percentile	-3.0 pp	-4.0 pp	1.0 pp
inequality measure	difference	composition	structural
total wage inequality	13.5 pp	10.1 pp	3.4 pp
upper tail wage inequality	7.6 pp	4.7 pp	2.9 pp
lower tail wage inequality	5.9 pp	5.4 pp	0.5 pp

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N=580,177.

Table 4: OLS Regressions: Wage Change on Occupational Change

region	period	sample	Δ wage	R-squared
whole sample	1980-2010	whole	0.84*	0.03
		below median	−0.07	0.00
		above median	1.66**	0.10
	1980-1990	whole	1.21***	0.10
		below median	−0.42	0.01
		above median	1.81***	0.24
	1990-2000	whole	0.27	0.00
		below median	0.04	0.00
		above median	0.67	0.02
	2000-2010	whole	0.14	0.00
		below median	0.07	0.00
		above median	0.2	0.00
weakly and negatively polarised	1980-2010	whole	0.21	0.00
		below median	−0.64	0.02
		above median	0.84	0.02
	1980-1990	whole	0.59	0.02
		below median	−0.42	0.01
		above median	1.22*	0.08
	1990-2000	whole	−0.01	0.00
		below median	0.15	0.00
		above median	0.09	0.00
	2000-2010	whole	−0.44	0.02
		below median	−0.72	0.04
		above median	−0.33	0.01
polarised	1980-2010	whole	0.41	0.01
		below median	−0.55	0.02
		above median	1.34	0.06
	1980-1990	whole	0.95**	0.06
		below median	−0.48	0.01
		above median	1.62***	0.20
	1990-2000	whole	−0.15	0.00
		below median	−0.25	0.00
		above median	−0.14	0.00
	2000-2010	whole	−0.02	0.00
		below median	−0.21	0.01
		above median	0.15	0.00
strongly polarised	1980-2010	whole	1.4 ***	0.10
		below median	0.82*	0.06
		above median	1.95***	0.15
	1980-1990	whole	1.47***	0.16
		below median	0.33	0.01
		above median	2.00***	0.26
	1990-2000	whole	0.87*	0.04
		below median	0.45	0.02
		above median	1.51*	0.07
	2000-2010	whole	0.54*	0.04
		below median	0.65*	0.07
		above median	0.41	0.02

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. (*|**|***) denote significance at the (10|5|1)% level of significance. N= 10,886,214.

Table 5: OLS Regressions: Wage Change on Occupational Change

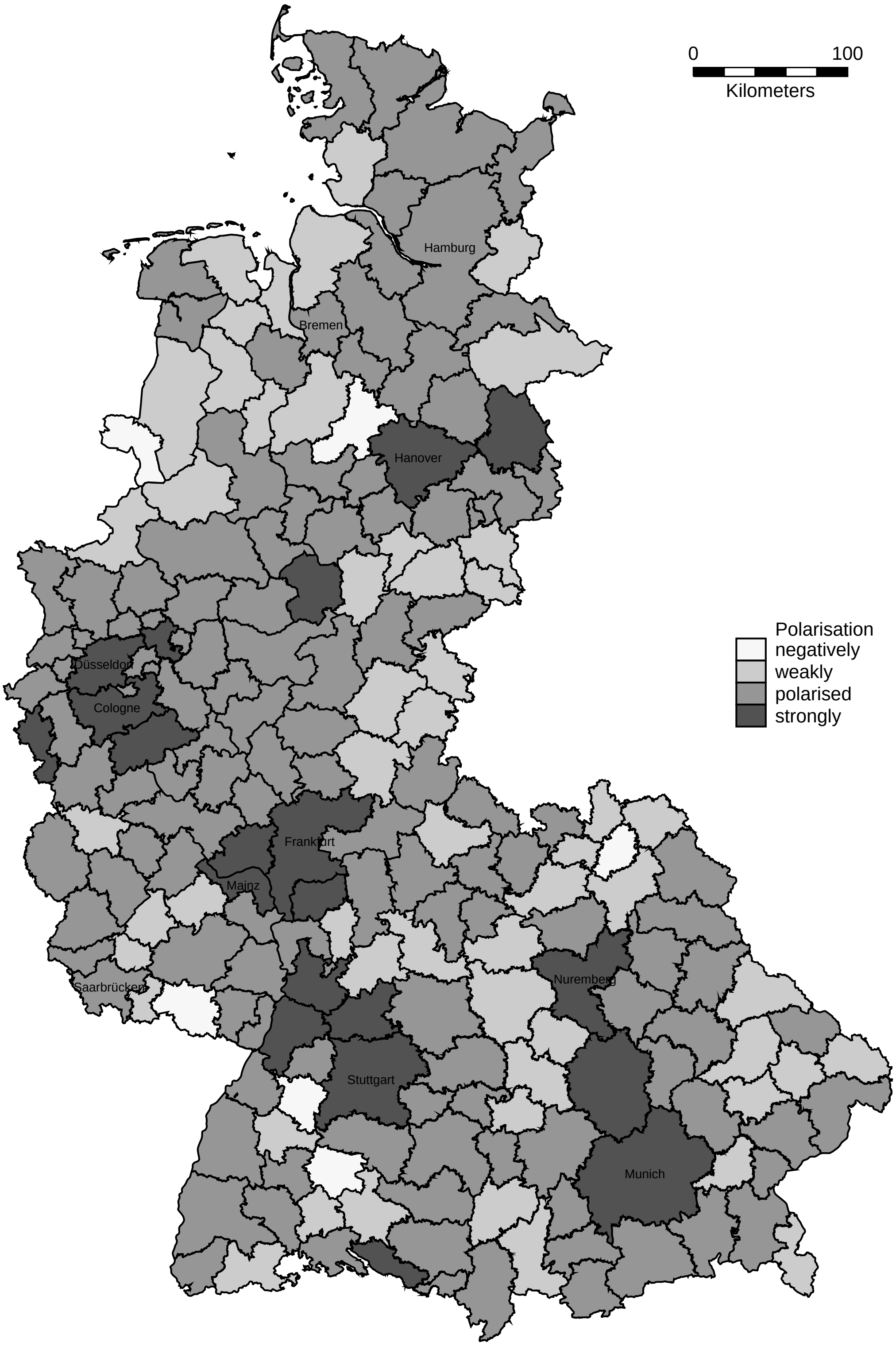
region	period	sample	Δ wage	Δ skills	initial educ	R-sq.
whole sample	1980-2010	whole	−1.64***	57.49***	30.16***	0.41
		below median	−2.13***	50.85***	47.41***	0.41
		above median	−2.21**	70.12***	35.5 ***	0.54
	1980-1990	whole	−0.71	51.55***	7.57***	0.46
		below median	−0.92	41.49**	11.06***	0.35
		above median	−0.44	54.22***	7.44***	0.60
	1990-2000	whole	−0.69*	31.5 ***	8.19***	0.34
		below median	−2.53***	46.96***	24.76***	0.54
		above median	−1.52**	44.86***	9.63***	0.57
	2000-2010	whole	−0.82**	11.23	7.37***	0.28
		below median	−0.75	8.26	10.71***	0.19
		above median	−1.16**	6.96	8.67***	0.47
weakly and negatively polarised	1980-2010	whole	−1.14**	41.89**	29.71***	0.30
		below median	−1.3	−24.41	22.6 *	0.21
		above median	−1.38	71.71***	31.53***	0.42
	1980-1990	whole	−0.54	38.78***	8.1 ***	0.29
		below median	−0.62	19.95	10.31***	0.13
		above median	−0.53*	45.5 ***	8.1 ***	0.44
	1990-2000	whole	−0.34	10.72	9.66***	0.32
		below median	−1.01*	12.05	20.06***	0.29
		above median	−0.42	19.93	8.88***	0.38
	2000-2010	whole	−0.7 **	−16.65	5.96***	0.20
		below median	−0.8	−38.25**	7.37	0.19
		above median	−0.62	−7.79	5.96***	0.21
polarised	1980-2010	whole	−1.68***	54.34***	28.41***	0.35
		below median	−2.27***	46.25*	45.62***	0.33
		above median	−2.05**	63.25***	32.6 ***	0.48
	1980-1990	whole	−0.51	41.34***	6.31***	0.33
		below median	−0.78	46.43**	11.82***	0.31
		above median	−0.04	42.29***	5.75***	0.47
	1990-2000	whole	−0.78	28.15**	7.4 ***	0.26
		below median	−2.88***	40.62*	26.6 ***	0.47
		above median	−1.82***	43.32***	8.75***	0.52
	2000-2010	whole	−0.87***	7.25	7.78***	0.30
		below median	−0.65	−1.97	8.11**	0.12
		above median	−1.15**	4.52	9.33***	0.52
strongly polarised	1980-2010	whole	−1.27**	51.35***	30.6 ***	0.46
		below median	−1.52***	46.93***	43.71***	0.51
		above median	−2.04**	65.01***	38.67***	0.57
	1980-1990	whole	−0.51	50.04***	8.12***	0.56
		below median	−0.18	47.45***	8.21***	0.44
		above median	−0.66	50.27***	9.91***	0.66
	1990-2000	whole	−0.36	26.1 ***	9 ***	0.38
		below median	−1.54*	28.56**	19.07***	0.48
		above median	−0.75	35.86***	11.17***	0.59
	2000-2010	whole	−0.28	7.18	6.8 ***	0.25
		below median	−0.5	10.65	12.69***	0.35
		above median	−0.75	1.26	8.65***	0.40

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. (*|**|***) denote significance at the (10|5|1)% level of significance. N= 10,886,214.

Appendix

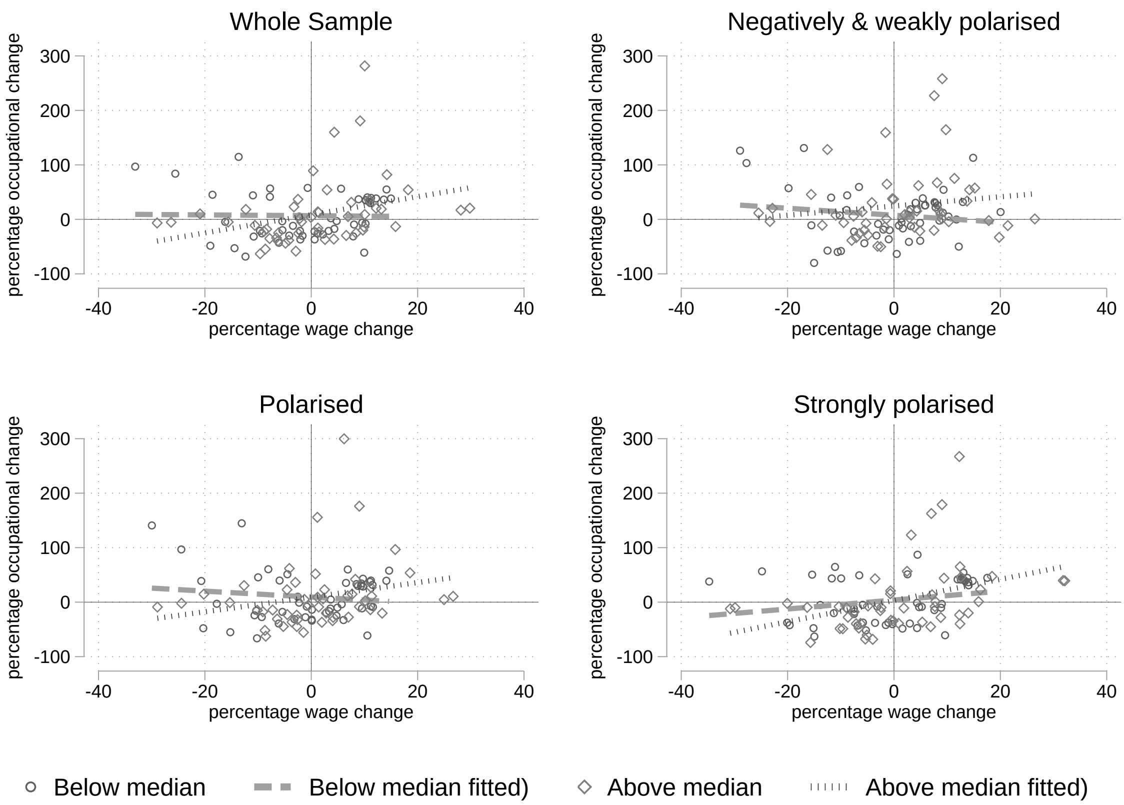
A Figures

Figure A1: Map of Job Polarisation in Germany



Source: Own illustration based upon Dauth (2014).

Figure A2: Link between Wage and Occupational change (1980-2010)



Source: 2% IABS Sample for full-time workers between the age of 20 and 60 years of age in Germany. N=10,886,214.

B Tables

Table B1: Wage Gap in 1980: Quantile Decomposition – Reference Group: Strongly Polarised LLM

wage	difference	composition	structural
85th percentile	7.3%	4.7%	2.6%
50th percentile	6.1%	2.0%	4.0%
15th percentile	7.9%	1.8%	6.1%
inequality measure	difference	composition	structural
total wage inequality	-0.7%	2.9%	-3.5%
upper tail wage inequality	1.2%	2.7%	-1.5%
lower tail wage inequality	-1.9%	0.2%	-2.0%

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N= 271,982, N= 171,815 for polarised LLM and N= 100,167 for strongly polarised LLM.

Table B2: Regional Wage Gap in 2010 – by Degree of Job Polarisation: Quantile Decomposition – Reference Group: Strongly Polarised LLM

wage	difference	composition	structural
85th percentile	19.1%	12.3%	6.7%
50th percentile	13.4%	5.7%	7.7%
15th percentile	10.5%	2.1%	8.5%
inequality measure	difference	composition	structural
total wage inequality	8.5%	10.3%	-1.7%
upper tail wage inequality	5.6%	6.6%	-0.9%
lower tail wage inequality	2.9%	3.7%	-0.8%

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N= 241,031, N= 149,302 for polarised LLM and N= 91,729 for strongly polarised LLM.

Table B3: Regional Growth Wage Gap in 2010: Quantile Decomposition – Reference Group: Strongly Polarised LLM

wage	difference	composition	structural
85th percentile	11.8 pp	7.6 pp	4.1 pp
50th percentile	7.3 pp	3.7 pp	3.6 pp
15th percentile	2.6 pp	0.2 pp	2.4 pp
inequality measure	difference	composition	structural
upper tail wage inequality	9.2 pp	7.4 pp	1.8 pp
lower tail wage inequality	4.5 pp	3.9 pp	0.5 pp
upper tail wage inequality	4.7 pp	3.5 pp	1.2 pp

Source: 2% IABS Sample for full-time workers between 20 and 60 years of age. N= 513,013.