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ABSTRACT

Occupation Growth, Skill Prices, and Wage Inequality*

This paper studies the relationship between changes in occupational employment, occupational wages, and rising overall wage inequality. Using long-running administrative panel data with detailed occupation codes, we first document that in all occupations, entrants and leavers earn lower wages than stayers. This empirical fact suggests substantial skill selection effects that are negative for growing occupations and positive for shrinking ones. We develop and estimate a model for prices paid per unit of skill in occupations, which incorporates occupation-specific skill accumulation over the career and endogenous switching across many occupations. Our results shed light on two important puzzles in prior literature. First, consistent with leading explanations for occupational employment changes, price and employment growth are positively related. Strong counteracting skill changes along the lines of our new empirical fact explain why occupational wages are unrelated to employment growth. Second, skill prices establish a long-suspected quantitative connection between occupational changes and the surge in wage inequality.

JEL Classification: J21, J23, J24, J31

Keywords: skill prices, selection effects, multidimensional skill accumulation, occupational employment and wages, administrative panel data, wage inequality

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1 Introduction

During the past decades, occupational employment has changed profoundly across Europe and the United States. A burgeoning literature has established fundamental shifts in labor demand as the most important cause of these changes (Autor et al., 2003; Goos and Manning, 2007; Acemoglu and Autor, 2011; Goos et al., 2014).[1] Yet, it remains puzzling that neither occupational wages nor wage inequality show a clear reflection of these demand shifts. First, occupational employment growth has been decoupled from occupational wage growth (Goos and Manning, 2007; Mishel et al., 2013; Green and Sand, 2015; Roys and Taber, 2019; Hsieh et al., forthcoming). Second, while wage inequality has risen dramatically over the same period that occupational employment has changed, there remains debate in the literature about how much of this can be attributed to demand shifts (Autor et al., 2008; Dustmann et al., 2009; Card et al., 2013; Firpo et al., 2013; Autor, 2019).

To solve these puzzles, we develop and estimate a model in which workers have occupation-specific skills that evolve endogenously over the career. Workers' optimal choices lead growing occupations to attract less skilled workers, which depresses these occupations' average wages. Shrinking occupations retain the most skilled parts of their workforce, lifting their average wages. The key distinction we make is between wages paid per constant unit of skill *(skill prices)*—which are directly affected by shifts in demand—and average occupational wages. Worker selection drives a wedge between the two. The evolution of skill prices will not be fully reflected in occupational wages and could even be neutralized or turn in the opposite direction. Moreover, between-occupation inequality will underestimate the impact of shifting occupational demand on wage inequality.

These mechanisms are consistent with stylized facts from our rich administrative panel data. As in the studies cited above, occupational wage growth and occupational employment growth bear no systematic relation with each other. At the same time, we find that individual workers' wage growth is substantially faster *within* expanding occupations. The discrepancy must stem from marginal workers. We newly document that workers who enter *any* occupation earn substantially less than incumbents. The

[1] We discuss the literature in detail in the next section.

same is true for workers leaving *any* occupation compared to stayers. Both effects are increasing in net occupation growth. The raw data thus reveal that net growth of an occupation will have a direct attenuating impact on average wages with selection operating in both directions. Growing occupations attract workers at the start of their careers, dragging down average wages. Declining occupations tend to shed workers who earn below-average wages, raising these occupations' average wages.

To quantify these effects, our economic model distinguishes between skill prices and skills. Workers have multidimensional skills that evolve heterogeneously across occupations and over the career. The model is explicitly based on Roy (1951) and therefore relaxes the exogenous mobility assumption (e.g., Abowd et al., 1999; Card et al., 2013; Cortes, 2016). That is, the choice of occupation may be driven by contemporaneous unobservable shocks. We employ a linear approximation to obtain an empirical formulation that is transparent and straightforward to estimate, even in settings with a large number of occupations. Our key identifying assumption is temporal stability of the skill accumulation function, which generalizes prior approaches. Accounting for this skill accumulation, the estimator then exploits workers' varying wage growth within and across occupations over time to identify changes in skill prices.

Our empirical analysis uncovers three main findings. First, there is a clear positive relationship between the development of skill prices and employment growth at the level of detailed occupations. This indicates that demand shifts were indeed the dominant drivers of both occupational employment and *skill-constant* wages over the past decades. Characterizing occupations by their task intensities, we find that the patterns are in line with routine-biased technical change (RBTC) as one of the important drivers of occupational demand.[2] More generally, the patterns are consistent with polarization, since employment and skill prices of broad occupation groups with high as well as low wages increased compared to mid-wage occupation groups.

The positive correlation of occupational employment with skill prices and the lack of a correlation with average wages means that skills must deteriorate in growing com-

[2]Note that this paper does not measure occupational demand or supply shocks directly. We instead infer from the co-movements of quantities and prices that these are consistent with demand shocks. Forces of occupational demand may include RBTC and related technical changes (e.g., Autor et al., 2003), international trade and offshoring (Autor et al., 2013; Goos et al., 2014), transformation of the industry structure (Bárány and Siegel, 2018), changes in consumption patterns (Autor and Dorn, 2013; Mazzolari and Ragusa, 2013), social skills content (Deming, 2017), among others.

pared to shrinking occupations. Our second main finding is that these skill changes from the estimation are consistent with those implied by our new empirical fact: lower-earning workers' net entry into growing and their net exit out of shrinking occupations fully account for the negative correlation between skill changes and employment growth. We term this the *marginal selection effect*. Viewed through the lens of our model, it stems from both entrants and leavers possessing lower skills than stayers in any occupation. We exploit the longitudinal dimension of the data to show that marginal selection conforms with economic notions of the underlying selection effects: The skill differences of entrants and leavers compared to stayers consist of differences in endowments, skill accumulation, and endogenous switching (staying) of those workers who experience negative (positive) shocks during their stint in an occupation.

Our third main finding is that occupational changes have driven much of the increase in wage inequality over the past decades. We decompose the trends in the wage distribution using our estimated model and find that changing skill prices in particular were a key driver of inequality. This impact is muted when studying between-occupation wage inequality in the raw data because average occupational wages do not systematically vary with skill prices, as implied by our second finding. Via reweighting, we also exploit the changing demographic structure to approximate some of the shifts of skill supply to occupations. These would have further raised inequality between occupations, had it not been for the strong selection effects.

This paper is structured as follows. Next, we describe the German SIAB data that we employ, relate to prior literature, and present the stylized facts motivating the course of our subsequent analysis. In the third section, we develop the model and estimation strategy. Section 4 presents the results on the evolution of skill prices, dissects the marginal selection effect, and reports on extensive robustness checks. In Section 5, we examine the impact of skill prices and skill selection on rising wage inequality. The last section discusses our findings' relationship to labor market institutions and sketches directions for further research.

2 Data, Literature, and Stylized Facts

We use the Sample of Integrated Labor Market Biographies (SIAB) provided by the IAB Institute at the German Federal Employment Agency. The SIAB is a 2% random sample of administrative social security records from 1975 to 2014. It is representative of 80% of the German workforce and includes employees covered by social security, marginal part-time workers, benefit recipients, individuals officially registered as job-seeking, and those participating in active labor market programs. The SIAB excludes the self-employed, civil servants, and individuals performing military service. Most notably, it contains individuals' full employment histories including detailed data on wages, industries, and occupations along with socio-demographics such as age, gender, or the level of education. The data is exact to the day as employers need to notify the employment agency upon changes to the employment relationship.

In order to work with a homogeneous sample throughout, we restrict the main sample to German men aged 25 to 54 years who are working full-time in West Germany. See Appendix A.1 for the reasons behind these choices and for details on the wider dataset construction. We will relax all of these restrictions in robustness checks. We transform the spell structure into a yearly panel by using the longest spell in any given year, adjusting wages appropriately for spells that do not last the entire year. Due to a cap on social security contributions, 12% of wages are right-censored at this ceiling; we follow imputation procedures in Dustmann et al. (2009) and Card et al. (2013). We inflate all wages to 2010 prices using the German consumer price index.

A key strength of the SIAB data is that it provides high-quality longitudinal information on workers' occupations. Until 2010, the SIAB Scientific Use File contains a consistent set of 120 occupations; we cannot use subsequent years because the classification changes drastically thereafter. Most of our analyses will be based on the raw 120 occupations. To ease interpretation, we also aggregate them into broader groups following Acemoglu and Autor (2011) and others. These comprise managers, professionals, and technicians (Mgr-Prof-Tech); sales and office workers (Sales-Office); production workers, operators and craftsmen (Prod-Op-Crafts); and workers in services and care occupations (Srvc-Care). See Table A.1 for the mapping of detailed occupations into these groups.

2.1 Wage Inequality and Changes in Occupational Employment

Two of the most important trends in developed countries' labor markets over the past decades have been a strong increase in wage inequality and a substantial reallocation of employment across occupations broadly characterized by polarization (for a summary see Acemoglu and Autor, 2011). As documented by, e.g., Spitz-Oener (2006), Dustmann et al. (2009), Card et al. (2013), and Goos et al. (2014), Germany is no exception to either phenomenon. Figure 1 reproduces both trends in our dataset.

Figure 1a shows the trends of wage percentiles over the 1985–2010 period normalized to zero in 1985; thereby reproducing Figure 1 in Card et al. (2013) up to the normalization, sample, and the percentiles. Inequality increased strongly and steadily both in the upper half, measured by the difference between the 85^{th} and the 50^{th} percentile of log wages, and in the lower half ($50 - 15$ difference). These trends have arguably led to a broader debate about inequality and opportunity,[3] as well as reignited policy efforts with regard to living wages and minimum wage regulations. For example, Germany introduced a statutory minimum wage in 2015; substantial raises to it are a constant source of public debate. Similarly, U.S. localities are in the process of or have already implemented a $ 15 minimum wage (e.g., Jardim et al., 2017), more than twice the nationwide minimum wage.

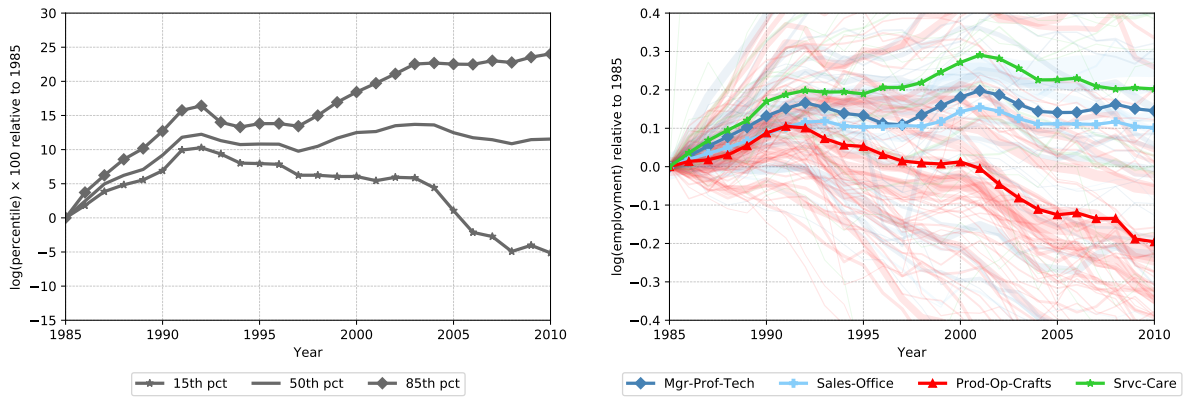
Using the year 1985 for the normalization once more, Figure 1b plots the trends in the logarithms of the detailed 120 occupations' employment (shaded lines) and the four aggregated groups (bold lines with markers). Employment in Production-Operators-Crafts occupations declined by more than 20 log points from a baseline share of over 60 percent, whereas the employment share of the other occupation groups increased. This trend has been termed "job" or "employment polarization" because Prod-Op-Crafts workers tend to be located in the middle of the occupational wage distribution (Goos and Manning, 2007). An important share of the declining employment in middle-paying occupations appears to be due to changes in technology (affecting codifiable routine-type jobs, see e.g., Autor et al., 2003) as well as international trade and offshoring (affecting manufacturing-type jobs, e.g., Autor et al., 2013). The

[3] Among others, see the research agenda by Chetty et al. (e.g., 2011, 2018), which has also spilled over to Europe and Germany (e.g., Cornelissen et al., 2018).

Figure 1: Evolution of wage inequality and occupational employment

(a) Wage percentiles

(b) Occupations' employment



Notes: The vertical axis in Panel 1a shows the 15th, 50th and 85th log wage percentile over time relative to 1985. The vertical axis in Panel 1b shows the log change in the number of employed workers within an occupation over time. Shaded lines in the background represent the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. The thickness of a shaded background line corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010.

resulting deterioration of employment opportunities—particularly severe for low and medium educated men—have been linked to societal trends of much wider concern.[4]

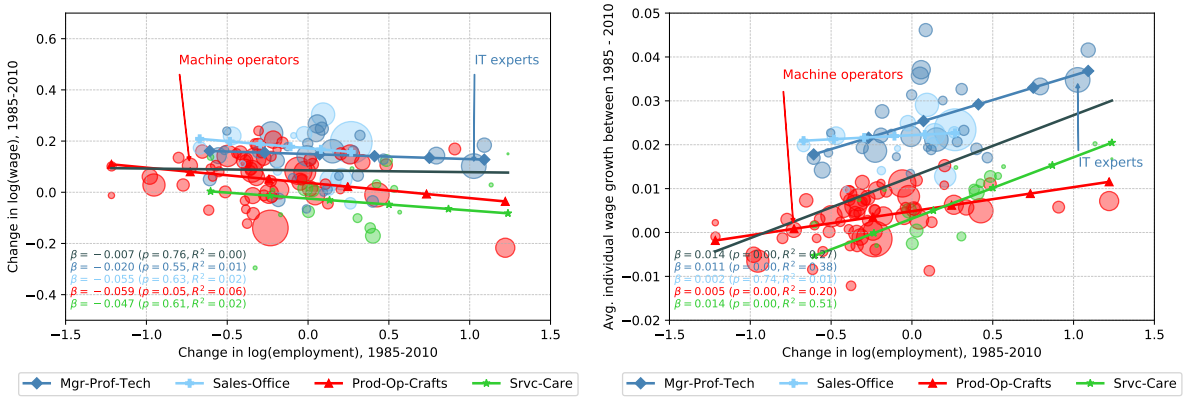
One may expect to see such shifts of the demand for different types of occupations directly in the wage distribution, not least because the wage and employment trends occurred largely in parallel (e.g., see Figure 1). There exists, however, surprisingly little quantitative evidence on the role of occupational change for the evolution of wage inequality: holding occupations' wages fixed at their initial levels and reweighting them with employment in subsequent decades, Goos and Manning (2007) show that composition effects due to employment polarization can account for a substantial part of changing wage inequality in the U.K. Very recently, Autor (2019) finds that in the U.S. a similar exercise explains only small shares of the income growth differentials across five education categories. Additionally accounting for the degree of urbanization comes close to matching the evolution of real wages of the non-college educated. For the German case, Dustmann et al. (2009) conclude that the rise of lower-half inequality was unlikely to stem from changes in demand. Card et al. (2013) run a set of Mincer regressions and incrementally add occupational identifiers, finding that the role of the latter for rising wage inequality is rather small.

[4]These include, among others, rising morbidity and mortality in midlife (Case and Deaton, 2015) as well as political polarization in various guises (Autor et al., 2016; Fetzer, forthcoming).

Figure 2: Correlation of changes in employment, average wages, and wage growth

(a) Average wage growth

(b) Individuals' wage growth



Notes: The vertical axis in Panel 2a shows the change in average wages between 1985 and 2010. The vertical axis in Panel 2b depicts individual wage growth averaged across years 1985 until 2010. The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure 2a hints at why these types of analyses tend to have limited explanatory power. The graph plots changes in employment against changes of average wages over the 1985–2010 period for each of our 120 occupations. Variation along the horizontal axis shows that employment changes are very substantial. Many occupations grew or shrank by more than 50 log points. Yet, movements of average wages are surprisingly small given the variation in occupation growth and the large increase of wage inequality. Therefore, between-occupation decompositions—such as wage regressions with occupation dummies or reweighting strategies—may attribute little of the trends in wage inequality to factors like changing skill prices and employment structure, and much of its increase to unexplained within-occupation inequality. More fundamentally, the employment and wage changes in Figure 2a are uncorrelated: occupations that grew a lot did not experience larger average wage increases than shrinking occupations. To pick the two highlighted examples, IT experts' employment increased by 102 log points or 178 % and their average wages grew by 10 %, just above the overall average. Machine operators—a prototypical occupation one would expect to be negatively affected by routine-biased technical change—shrank by 73 log points or 51 %. Yet, their average wages grew by the same amount as those of IT experts.

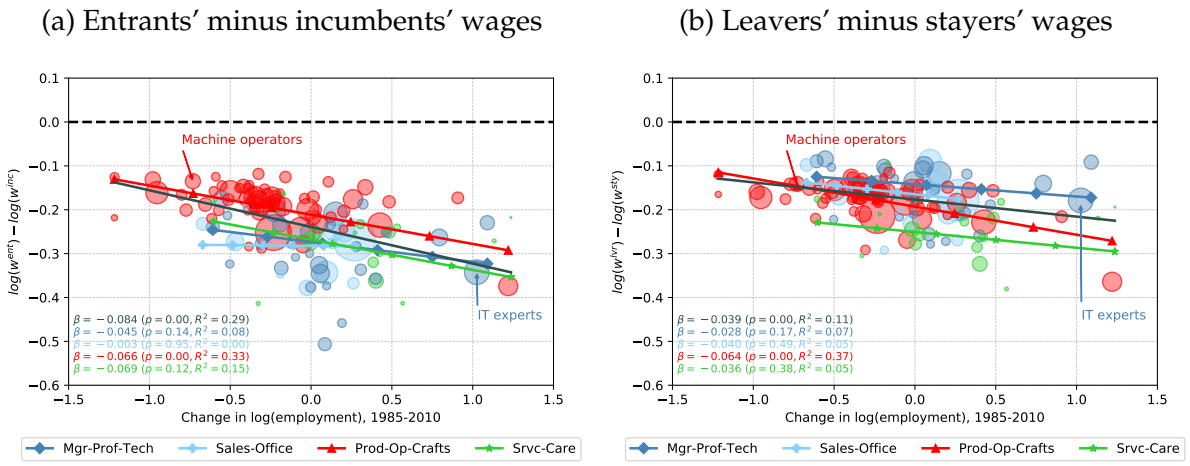
Within the broader groups, the non-correlation between wage and employment growth even turns negative for the lower-earning Prod-Op-Crafts and Srvc-Care occupations. This is consistent with the regressions reported by Dustmann et al. (2009) in their Section IV.D, which led them to conclude that demand shifts were unlikely to drive lower-end inequality. The finding of little or negative correlation between occupational wage and employment growth is not confined to Germany. Hsieh et al. (forthcoming) and Roys and Taber (2019) document correlations between the growth rates of occupational employment and wages in the U.S. that are very small and positive or zero, respectively. Employment in low-skill occupations increased in the U.K. and Canada, while at the same time wages in these occupations dropped compared to routine occupations (Goos and Manning, 2007; Green and Sand, 2015). Next to the role that occupations have to play for wage inequality, this begets the more fundamental question of whether, on aggregate, shifts in demand versus supply of labor to different occupations were the dominant factor for the changes of the employment structure.[5] We will find that, while the latter may have a role to play, the data strongly suggest that demand changes along the lines of routine-biased technological change or international trade are important.

2.2 Individual-Level Wage Growth and Selection

As a first pass, Figure 2b shows that there is a strong positive correlation between employment and *individual-level* wage growth. The horizontal axis is the same as in Panel a whereas the vertical axis plots the average annual wage growth of workers who stayed in their occupation for any two consecutive years. Wage growth rates within occupations clearly line up with their employment growth. Abstracting from other factors that we will control for later—most notably, occupation- and age-specific returns to experience—the main factor leading to the stark differences between the two panels of Figure 2 may well be differential selection into occupations. Put differently, demand shifts could indeed be driving the changes of employment and prices paid for skilled labor across occupations, but negative selection of entrants into growing occupations shrouds this relation when looking at average occupation-specific wages. The

[5] E.g., Glitz and Wissmann (2018) argue that a declining supply of medium versus low-skilled young workers in Germany was responsible for part of the rising lower-end inequality depicted in Figure 1a.

Figure 3: Selection into and out of occupations



Notes: The vertical axis in Panel 3a shows the average wage of an entrant to an occupation relative to the average wage of incumbents. The average is taken across years 1985 until 2010. The vertical axis in Panel 3b shows the average wage of a worker leaving an occupation next period relative to the average wage of stayers. The average is taken across years 1985 until 2009 to avoid all workers being leavers at the sample end. The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

underlying occupational prices would be spreading out more than the average occupational wages, which are captured in the above-discussed decomposition analyses.

Data limitations have prevented a more thorough analysis of the presence and magnitude of such selection effects. In particular, the main sources in the U.S. are repeated cross-sections (CPS, Census) or longitudinal data too small in size for investigating individual-level dynamics across detailed occupations (PSID, NLSY). The SIAB data allow us to track occupational biographies over the entire career. Figure 3 gives more direct evidence on the importance of selection effects by plotting employment changes against the wage differentials between marginal workers who switch and inframarginal workers who stay in their occupations.[6]

The vertical axis of Figure 3a shows the difference between entrants and incumbents. An occupational entrant is defined as anybody who is newly observed in the occupation in the current period. He could be joining the labor force for the first time, switching from a different occupation, or entering from unemployment or outside of the labor force. The difference between this group and incumbents is strongly negat-

[6] McLaughlin and Bils (2001) perform a related exercise with a coarser set of industry sectors in the PSID data. They report similar results on wage differences but struggle to find a correlation with changes in employment shares, possibly due to the small sample size.

ive and strongly declining in occupation growth. The latter suggests that skill selection is the reason for the wage gaps—rather than, e.g., delayed wage contracting (Lazear, 1981)—since it is consistent with a situation where the skill pool that growing occupations can draw from shrinks with the extent of their expansion. Returning to our example, a machine operator might find it attractive to switch careers and become an IT expert in reaction to more lucrative employment opportunities there. It is not unreasonable, either, because controlling complex machines often involves some programming and algorithmic knowledge. However, given that he preferred a different career before, it is likely that the former machine operator's specific skills are such that he will obtain a lower wage than incumbent IT experts.

In principle, the patterns in Figure 3a could be generated if occupation choice only happened at labor market entry in combination with substantial returns to experience. If this was the sole effect, however, we would expect that the wages of workers leaving their occupations would be higher than the wages of those who stay on. Put differently, in such a scenario individuals dropping out of our sample after age 54 should dominate the difference between leavers and stayers. Figure 3b shows that the opposite is the case. As for entrants, marginal workers have substantially lower wages than those who stay on. Again, the difference is increasing in employment growth. Put differently, only the lowest-skilled workers leave fast-growing occupations. All patterns in Figure 3 persist when controlling for age and education or considering only moves between occupations, i.e., discarding switches to or from non-working states.[7] These pieces of evidence indicate that the wage gap is not just due to entrants being at an earlier stage of their career compared to incumbents.

The prominent models in the literature on occupational changes have difficulties matching Figure 3 because they feature one-dimensional skills (e.g., Acemoglu and Autor, 2011; Autor and Dorn, 2013). One-dimensionality ensures tractability in general equilibrium, which led to many important insights. The flipside is that it leads to a hierarchical ranking of occupations by skill, implying both that switchers to higher-ranked occupations leave lower-ranked occupations from above and that switchers

[7]See the figures in Section A.2 of the Appendix. When controlling for covariates, the magnitudes of the differences become smaller on average and the slopes tend to become more pronounced. As one would expect, considering only switches that happen directly between occupations has an attenuating effect on all patterns, but the qualitative pattern is always the same and highly significant.

from higher-ranked occupations enter lower-ranked occupations from above (Papageorgiou, 2014). This is hard to square with the fact that even entrants and leavers in low-wage occupations generally earn less than incumbents and stayers, respectively.[8]

Instead, the patterns in Figure 3 call for a Roy-like approach to model sorting across occupations, with workers who possess specific skills such that both entrants and leavers are less skilled than incumbents and stayers. For example, in a model with two occupations and two skill types, Papageorgiou (2014) shows that switching workers earn wages below the average in the occupation they are leaving as well as the one they are entering so long as they do not have an absolute advantage in both occupations. Young (2014) calls this the case where "comparative advantage is aligned with absolute advantage", which leads to declining skills in growing sectors. The conditions in Papageorgiou and Young are sufficient for marginal workers to have lower skills than inframarginal workers and for occupation growth causing skills to deteriorate. The necessary conditions are weaker; they only require that skills across occupations are not perfectly correlated and thus multidimensional (e.g., Heckman and Sedlacek, 1985). This level of generality forms our point of departure for the next section, where we develop a model that allows us to quantify these effects.

3 Estimating Skill Prices under Optimal Occupational Choice

This section presents our model to estimate skill prices, which enables us to distinguish price from selection effects when occupational wages change over time. We start by describing how we can exploit workers' occupation choices in a classic Roy (1951) model to estimate the growth of potential wages across sectors. In Section 3.2, we outline our decomposition of wages into prices and workers' skills along with a discussion of our main identifying assumptions. We then show how the model lends itself to a straightforward estimation strategy, which is feasible even for the 120 occupations $\times$ 35 years in our application. In Section 3.4, we bring the estimation strategy to its

[8]Honing in on evidence similar to Figure 3, we explicitly test and reject the model of one-dimensional skills in Online Appendix B.2. We do however obtain some evidence for a hierarchy between Mgr-Prof-Tech and the other broad occupation groups. This aspect of our data is consistent with the findings in Groes et al. (2014).

limits in a series of Monte Carlo experiments and show how to incorporate additional features, for example, non-pecuniary job attributes in the generalized Roy model.

3.1 A Tractable Model of Sector Choice

There are $k = 1, \ldots, K$ distinct occupations. At time t a worker i earns potential wages $W_{i,t} = \begin{pmatrix} W_{1,i,t} & W_{2,i,t} & \ldots & W_{K,i,t} \end{pmatrix}$. Most of our analysis will be in relative terms and we use lowercase letters to denote the logarithm of a variable. As in Roy (1951), we assume that workers maximize their incomes by choosing the occupation in which they earn the highest wage:

$$w_{i,t} = \max\{w_{1,i,t}, \ldots, w_{K,i,t}\} = \sum_{k=1}^{K} I_{k,i,t} w_{k,i,t}, \tag{1}$$

where $I_{k,i,t} \equiv \mathbb{1}[\max_{j=1,\ldots,K}\{w_{j,i,t}\} = w_{k,i,t}] = \mathbb{1}[w_{k,i,t} \geq w_{j,i,t}\ \forall j \neq k]$ is a choice indicator for occupation k.

Ignoring the source of changes in potential wages in this subsection, we begin by considering the effect of marginal changes thereof on realized wages. By the envelope theorem,[9] such changes will only have marginal effects on realized wages because occupation choices are the solution to the optimization problem (1). Put differently, workers do not enjoy discrete gains in realized wages when switching occupations in response to marginal changes of potential wages. For notational simplicity, we suppress the case of indifference at the prevailing wage (it will be trivially captured once we move to discrete wage changes immediately below) and write the marginal change in worker i's realized wage at time t as:

$$dw_{i,t} = \begin{cases} dw_{1,i,t} & \text{if } I_{1,i,t} = 1 \\ \vdots & \\ dw_{K,i,t} & \text{if } I_{K,i,t} = 1 \end{cases}$$

[9] The optimization problem (1) fulfills the conditions for the general envelope Theorem 2 of Milgrom and Segal (2002). Incidentally, Milgrom and Segal derive the change in their general value function as an integral over the choices similar to our Equation (3). Böhm (2019) provides a derivation similar to ours in a static setting; he also provides special cases that do not even require the envelope theorem.

or, equivalently,

$$dw_{i,t} = I_{1,i,t}dw_{1,i,t} + \ldots + I_{K,i,t}dw_{K,i,t} = \sum_{k=1}^{K} I_{k,i,t}dw_{k,i,t}. \tag{2}$$

In order to understand wage changes between discrete time periods, we integrate over Equation (2) from potential wages $\{w_{1,i,t-1}, \ldots, w_{K,i,t-1}\}$ to $\{w_{1,i,t}, \ldots, w_{K,i,t}\}$. With a slight abuse of notation—made precise in Appendix B.1.1—we obtain

$$\Delta w_{i,t} = \sum_{k=1}^{K} \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_{k,i,\tau}dw_{k,i,\tau}. \tag{3}$$

This result is rather intuitive: if a worker stays in his occupation k' between two points in time ($I_{k',i,t-1} = I_{k',i,t} = 1$), his realized wage change is equal to the change in his potential wage in the chosen occupation (i.e., $\Delta w_{i,t} = \Delta w_{k',i,t}$). If the worker switches from some other occupation k'' to k', ($I_{k'',i,t-1} = 1$, $I_{k',i,t} = 1$), his realized wage change is made up of two hypothetical components. One part stems from the wage change he would have experienced had he stayed in his previous occupation. The other part is the corresponding wage change had he been in the destination occupation all along. The relative size of both parts is determined by the point of indifference, i.e., the potential wages $w_{k',i,\tau^*} = w_{k'',i,\tau^*}$ so that $\Delta w_{i,t} = (w_{k',i,t} - w_{k',i,\tau^*}) + (w_{k'',i,\tau^*} - w_{k'',i,t-1})$. This trivially simplifies to $\Delta w_{i,t} = w_{k',i,t} - w_{k'',i,t-1}$, which is exactly the wage change that the definition of the realized wage (1) implies. The fact that only potential wages in his origin and destination occupations matter for the observed wage change makes sense given that the worker has comparative advantage in both of these occupations.

In empirical analyses, Equation (3) is directly observable for occupation stayers. That is, occupation choices on the right-hand-side and realized wage changes on the left-hand-side appear directly in the data. For switchers, we need to approximate the choices because we cannot observe switchers' point of indifference. We linearly interpolate the choice indicators for $\tau \in (t-1, t)$:

$$I_{k,i,\tau} \approx I_{k,i,t-1} + \frac{I_{k,i,t} - I_{k,i,t-1}}{w_{k,i,t} - w_{k,i,t-1}}(w_{k,i,\tau} - w_{k,i,t-1}) \tag{4}$$

Defining $\bar{I}_{k,i,t} \equiv \frac{1}{2}(I_{k,i,t} + I_{k,i,t-1})$ and combining Equations (3) and (4), we obtain

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta w_{k,i,t}. \tag{5}$$

A detailed derivation is in Appendix B.1.2. The intuition of Equation (5) after the approximation is the same as before: if a worker stays in his occupation, his wage gain is the change of his potential wage in that occupation. If the worker switches, he obtains equal parts of the origin and destination occupations' wage change. The strength of this result is that it allows to recover potential wage changes—even for switchers when occupational choice is endogenous—from panel data on occupation choices and realized wages, allowing for many occupations due to its simplicity. In particular, mean changes of potential wages can be recovered from a regression of first-differenced wages on "average" occupation choices $\{\bar{I}_{k,i,t}\}_{k=1}^{K}$. This hinges, of course, on the quality of the approximation. We first note that (4) is not an approximation at all for the majority of workers who stay in their occupation. To assess the impact of those who switch, we run a large set of Monte Carlo simulations. We will report on them in Section 3.4, noting here that the approximation in (4) is not a first-order concern.

3.2 Price and Skill Changes

We denote potential wages as the product of workers' skills $S_{i,t} = \begin{pmatrix} S_{1,i,t} & S_{2,i,t} & \dots & S_{K,i,t} \end{pmatrix}$ and the occupation-specific prices paid for a unit of skilled labor $\Pi_t = \begin{pmatrix} \Pi_{1,t} & \Pi_{2,t} & \dots & \Pi_{K,t} \end{pmatrix}$ that prevail in the economy.[10] The worker's potential log wages become for all $k \in \{1, \dots, K\}$:

$$w_{k,i,t} = \pi_{k,t} + s_{k,i,t} \tag{6}$$

The framework outlined in the previous section relies on differences; we thus do not place any restrictions on the initial levels of prices or skills. The empirical challenge is to disentangle changes in prices from changes in skills. In order to do so, we impose

[10] Contrary to previous literature, we do not draw an explicit distinction between workers' skills and occupational tasks because we do not need the tasks as a dimension-reduction device. Our formulation is, however, perfectly general and nests, for example, the wage setting model in Firpo et al. (2013). We will eventually use tasks information to help interpret our results and connect back to previous work.

some structure on the skill accumulation process, which we model by learning-by-doing on the job. Its speed is occupation-specific and depends on observables; working in one occupation k' impacts subsequent skills in all other occupations. In particular, we assume that for all $k \in \{1, \ldots, K\}$:

$$\Delta s_{k,i,t} = \sum_{k'=1}^{K} I_{k',i,t-1} X'_{i,t-1} \Gamma_{k',k} + u_{k,i,t}. \tag{7}$$

The vector $X_{i,t-1}$ consists of a constant and observable variables controlling the speed of skill acquisition or depreciation via the vector $\Gamma_{k',k}$. Note that this formulation contains a full set of interactions of the skill accumulation coefficients $\Gamma_{k',k}$ with the covariates $X_{i,t-1}$. The summation term in (7) thus maps the previous occupation choice k' interacted with $X_{i,t-1}$ into skill changes in all potential occupations in the current period.

Our key identifying assumption is that the systematic part of the skill accumulation function (7) is time invariant. This is embodied in the fact that $\Gamma_{k',k}$ does not carry a time-subscript. Our condition is implied by an assumption made in virtually the entire literature studying occupational changes (e.g., Acemoglu and Autor, 2011; Firpo et al., 2013; Gottschalk et al., 2015; Cortes, 2016; Young, 2014; Bárány and Siegel, 2018; Böhm, 2019; Yamaguchi, 2018) that differences in returns to worker characteristics over time are due to changes in the returns to skills rather than changes in skill endowments. That assumption pins down the levels and growth rates of skills; ours does the same for the growth rates only. Our requirement is thus weaker in the sense that we do not place a restriction on the initial skill levels when entering an occupation[11] or on the precise contents of work within occupations, which may have changed (Spitz-Oener, 2006). We also richly model the skill accumulation function, most importantly including fully stratified occupation choices $I_{k',i,t-1}$ and ages $X_{i,t-1}$ among the observables, so that composition changes of workers' learning-by-doing are flexibly accounted for. Conditional on these observables, we do however assume that the speed of learning

[11] This is along with other papers using panel data (Cortes, 2016; Cavaglia and Etheridge, 2017). Removing the restriction on levels seems important in light of the first-order shifts in some observable characteristics. E.g., Carneiro and Lee (2011) show that in the U.S., the average skill of college graduates declined substantially as enrollment rates increased between 1960 and 2000. One may expect similar effects in Germany given that college completion rates doubled between the older and younger cohorts in our analysis.

on the job has not changed over time. For example, a car mechanic in 2010 may well spend more time fixing electronics than his counterpart in 1975. A secretary will send e-mails rather than typing letters. But there is no temporal change in the speed at which these people get better at their jobs from one year to the next.

Our identifying assumption implies that within occupations, the ratio of wage growth across different groups remains constant over time. We check this in Figure 4, which plots the year-to-year wage growth of 25-34 year-olds (Panel 4a) and 35-44 year-olds (Panel 4b) minus the wage growth of 45-54 year-olds. We subtract the overall mean everywhere so that all eight lines should be flat at zero under our assumption. The lines in the right panel come very close to it. The left panel is somewhat noisier, particularly for the group of managers, professionals, and technicians. The noise is not too surprising given that many in this group enter the labor market at ages 25-34 and initial wage growth should be more susceptible to business cycles.[12] For example, the largest changes of wage growth across age groups can be found during the dotcom bubble in the late 1990s.[13]

Another identification strategy is to assume that seasoned workers' average skill growth is zero ("flat spot identification", Heckman et al., 1998), allowing us to interpret all occupation-specific wage growth over the decades as price growth (but still incorporating endogenous choices as derived in Equation (5)). We will explore this as a robustness check that yields qualitatively similar results to our main specification.

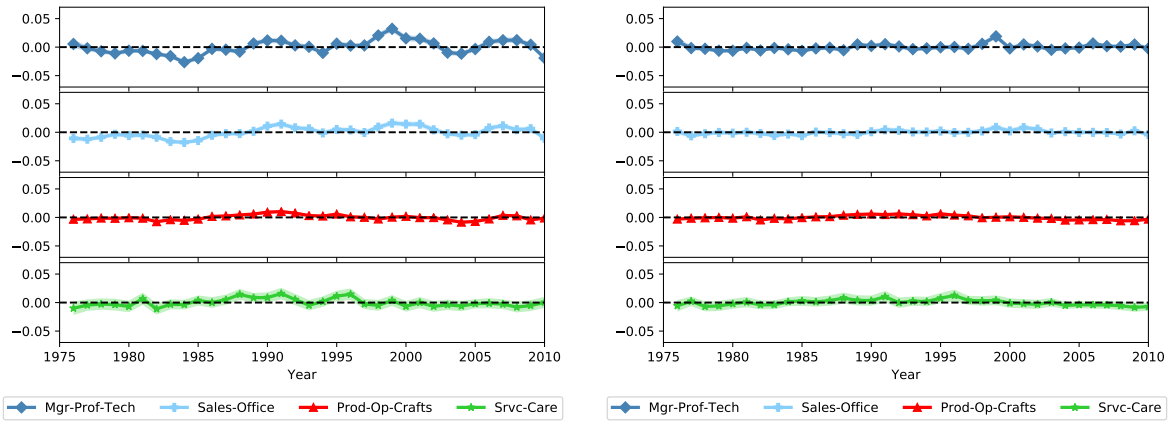
In terms of unobservables, we allow the joint distribution function $F(u_{1,i,t}, \ldots, u_{K,i,t})$ to vary freely across occupations. For example, idiosyncratic skill shocks can be correlated among similar occupations in an unrestricted way. The restrictions we do impose are independence across individuals and an identical conditional distribution over time. That is, each skill shock's mean, conditional on all predetermined variables, is

[12] Consistent with that argument, Liu et al. (2016) find that the probability of an initial mismatch between jobs and workers is strongly countercyclical. This feeds into lower initial wages as well as persistently lower wage growth in subsequent periods.

[13] As an alternative for the 120 occupations, we split the sample in the middle (1993) and plot the change in log employment against the change in wage growth of young (age 25–34 or 35–44) minus old (45–54) workers in the resulting two periods. Naturally, there is more variation than for the four broad occupation groups but most of the occupations have very modest changes in relative wage growth rates and we cannot detect substantive patterns among them. See Online Appendix A.3.

Figure 4: Individual wage growth relative to 45–54 year olds

(a) 25–34 year olds (b) 35–44 year olds



Notes: The lines show average individual wage growth from $t-1$ to t by year of 25–34 (Figure 4a) and 35–44 (Figure 4b) year olds minus average wage growth of 45–54 year olds. Results are centered at zero to show trends over time. The shaded areas around the four lines are 95% confidence intervals. The four groups are based on an aggregation of detailed occupations in the SIAB SUF as described in Appendix Table A.1.

assumed to be zero:

$$E\left[u_{k,i,t} \mid I_{k',i,t-1}, X_{i,t-1}\right] = 0 \;\forall\; k', k \in K$$

These restrictions are considerably weaker than in existing fixed effects approaches (e.g., Abowd et al., 1999; Card et al., 2013; Cortes, 2016), which require mean zero shocks conditional on *contemporaneous* variables ('exogenous mobility assumption'). We can do this because we explicitly derived wage growth when workers endogenously choose occupations in Section 3.1. We will see that this is important in the results below. Our restrictions are also more flexible than the types of assumptions that previous estimations of the Roy model (Heckman and Sedlacek, 1985) or of fully specified structural models (Lee and Wolpin, 2006) have invoked. In particular, we do not impose a parametric functional form for the distribution of unobservables.

3.3 Estimation of the Model and Interpretation of Coefficients

Under the assumptions we have made, we can compare price growth across different periods. The simplest intuition is that we can estimate the skill accumulation parameters $\Gamma_{k',k}$ in a base period $t = 0, \ldots, T_{\text{base}}$ and use these to predict individuals' skill growth in $t = T_{\text{base}} + 1, \ldots, T$ given their occupation choices. Subtracting predicted

skill changes from realized wage growth and aggregating over all workers in an occupation yields price growth.

More formally, we substitute (7) into the equation for wage growth (5) to obtain our baseline estimation equation:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \left(\Delta \pi_{k,t} + \sum_{k'=1}^{K} I_{k',i,t-1} X'_{i,t-1} \Gamma_{k',k} + u_{k,i,t} \right) \tag{8}$$

Our goal is to estimate the parameters in $\Delta \pi_{k,t}$ and $\Gamma_{k',k}$ for all $k, k' \in K$. As it stands, they are not separately identified from each other because of the intercept in $X_{i,t-1}$, which represents a level shifter for the speed of skill accumulation in each occupation by virtue of the interaction with last period's occupational choice indicator. We can, however, compare the speed of skill price growth in different periods of our sample. Having to distinguish between price and skill growth is a general challenge of panel-data based estimations. We make the necessity for this explicit and will abstract from any short-term influences by using an entire decade (1975–1985) as the base period.[14] Figure A.3 in the Appendix depicts the employment and wage trends also for our base period. The decade 1975–1984 covers the entire business cycle. Between 1976 and 1979, average GDP growth was almost 4% annually; it then was below one percent on average until 1984 and picked up again in 1985. Furthermore, the resulting analysis period of 1985–2010 is the same as in Card et al. (2013).

In practice, we set $\Delta \pi_{k,t} = 0 \; \forall \; k \in \{1, \dots K\}, t \in \{1, \dots, T_{\text{base}}\}$. The interpretation of $\Delta \pi_{k,t}, \; t \in \{T_{\text{base}} + 1, \dots, T\}$ changes depending on whether this holds as an assumption or whether it is better viewed as a normalization. The simplest interpretation obtains in the former case; i.e., skill prices during the base period were indeed constant. It is clear that the skill accumulation coefficients $\Gamma_{k',k}$ in this case will be identified from the base period. Accordingly, the estimates of $\Delta \pi$ can be interpreted as actual changes of skill prices for $t > T_{\text{base}}$.

Now suppose that constant skill prices during the base period are a poor approximation; i.e., there were substantial systematic changes between $t = 1$ and $t = T_{\text{base}}$. This implies that our estimated skill price changes in subsequent years are accelera-

[14] As an alternative, Cortes (2016) and Cavaglia and Etheridge (2017) do not use a base period and thus implicitly set one of the skill accumulation parameters to zero (details in Appendix B.4).

tions or decelerations relative to their (unknown) trends during the base period. To be precise, in the absence of other confounding factors, the estimated skill accumulation coefficients will be $\hat{\Gamma}_{k',k} = \Gamma_{k',k} + \frac{1}{2}\overline{\Delta\pi_{k,base}} + \frac{1}{2}\overline{\Delta\pi_{k',base}}$. Accordingly, the skill price estimates for $t = T_{\text{base}+1}, \ldots, T$ identify $\Delta\hat{\pi}_{k,t} = \Delta\pi_{k,t} - \overline{\Delta\pi_{k,base}}$. In our discussion, we mainly stick with the easier literal interpretation of the parameter estimates. We will note the caveat on several occasions, taking particular care to point out instances where the acceleration/deceleration interpretation does make a substantive difference.

Turning to the estimation of the model, we first obtain a standard regression equation from (8) by writing out the summations:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta\pi_{k,t} + \sum_{k=1}^{K}\sum_{k'=1}^{K} \bar{I}_{k,i,t}I_{k',i,t-1}X'_{i,t-1}\Gamma_{k',k} + v_{i,t} \ , \tag{9}$$

where $v_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t}u_{k,i,t}$. It is clear from this definition that v and the regressors are correlated since a large innovation to skills in a particular occupation makes it more likely that choosing this occupation happens to be optimal. First, we argue that a basic OLS regression of (9) will often yield good results. We then outline an instrumental variables strategy.

The regression (9) is a saturated skill model including all combinations of occupation choices $I_{k',i,t-1}$ and $I_{k,i,t}$. In the base period, the regression gives:

$$E\left[\Delta w_{i,t}\middle|\left\{I_{k,i,t}, I_{k,i,t-1}\right\}_{k=1}^{K}, X_{i,t-1}\right] =$$

$$E\left[\sum_{k=1}^{K}\sum_{k'=1}^{K} \bar{I}_{k,i,t}I_{k',i,t-1}X'_{i,t-1}\Gamma_{k',k} + v_{i,t}\middle|\left\{I_{k,i,t}, I_{k,i,t-1}\right\}_{k=1}^{K}, X_{i,t-1}\right]$$

The fully interacted base period regression identifies this conditional expectation function and therefore yields expected skill changes $E\left[\Delta s_{k,i,t}\middle|\left\{I_{k,i,t}, I_{k,i,t-1}\right\}_{k=1}^{K}, X_{i,t-1}\right]$. Defining $\nu_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t}\left[\Delta s_{k,i,t} - E\left[\Delta s_{k,i,t}\middle|\left\{I_{k,i,t}, I_{k,i,t-1}\right\}_{k=1}^{K}, X_{i,t-1}\right]\right]$, the regression equation in the analysis period can be re-written as:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta\pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t}E\left[\Delta s_{k,i,t}\middle|\left\{I_{k,i,t}, I_{k,i,t-1}\right\}_{k=1}^{K}, X_{i,t-1}\right] + \nu_{i,t} \tag{10}$$

Conditional on $X_{i,t-1}$ and any combination of $I_{k',i,t-1}$ and $I_{k,i,t}$, the expectation of $E\left[\Delta s_{k,i,t} - E\left[\Delta s_{k,i,t} \middle| \{I_{k,i,t}, I_{k,i,t-1}\}_{k=1}^{K}, X_{i,t-1}\right]\right]$ is zero by construction. The point here is that in the base period we already estimate the wage changes of occupation switchers, including the skill accumulation as well as idiosyncratic skill shocks. Therefore, if $E\left[\Delta s_{k,i,t} \middle| \{I_{k,i,t}, I_{k,i,t-1}\}_{k=1}^{K}, X_{i,t-1}\right]$ is consistently estimated in the base period, the error term in regression (10) is uncorrelated with the regressors $\bar{I}_{k,i,t}$ and changes in skill prices are identified under our assumptions.

An alternative approach to removing the bias in Equation (8) is by instrumenting the regressors $\{\bar{I}_{k,i,t}\}_{k=1}^{K}$ with their predetermined components $\{I_{k',i,t-1}\}_{k'=1}^{K}$, which are not a function of $u_{k,i,t}$. As in dynamic panel data models (Anderson and Hsiao, 1982; Arellano and Bond, 1991), we could in principle use long occupational histories as instruments. It is well-known, however, that this leads to issues with many weak instruments (e.g., Newey and Windmeijer, 2009). We thus instrument $\bar{I}_{k,i,t}$ to get $\pi_{k,t}$ with $I_{k,i,t-1}$, i.e., individual i's occupation choice in the year before in order to have an instrument for skill price changes between years $t-1$ and t. For skill changes, we instrument $\bar{I}_{k,i,t} I_{k',i,t-1} X'_{i,t-1}$ with the occupational history in the two years preceding $t-1$, i.e., $I_{k,i,t-2} I_{k',i,t-1} X'_{i,t-1}$ and $I_{k,i,t-3} I_{k',i,t-1} X'_{i,t-1}$. This amounts to $(T - T_{base}) \cdot K + 2 \cdot K^2 \cdot L$ instruments, where L is the number of elements in X_t. This strategy will not be feasible for large K but we will use the IV as a major alternative specification for the four broad occupation groups.

Finally, notice that the OLS estimates $\hat{\Gamma}_{k',k}$ may not correspond to the structural skill accumulation parameters in Equation (9). The reason is that the $\hat{\Gamma}_{k',k}$ are the averages of skill changes, whether due to systematic accumulation or due to idiosyncratic shocks, of $k' \neq k$ switchers or $k' = k$ stayers. Since switching or staying is endogenous, we expect the skill accumulation parameters to be overestimated in the OLS. The IV does not have this problem and we expect skill accumulation estimates for stayers to be unbiased. But the first stage may be weak for predicting occupational switches and thus it may also be difficult in the IV to obtain the correct structural estimates of the off-diagonal elements in $\Gamma_{k',k}$.

3.4 Performance of the Estimation Strategy and Model Extensions

We test the limits of our estimation method in a broad range of Monte Carlo experiments, also exploring extensions of the underlying economic model. Furthermore, we compare the performance of our approach to an alternative that uses occupation-specific fixed effects pioneered by Cortes (2016). We limit ourselves to a short description of the results, all details can be found in Section C of the Appendix.

In the Monte Carlo simulations, we aim to create a fairly realistic setting. We draw a sample of occupations and wages at labor market entry from our SIAB dataset. The remaining potential wages are drawn from truncated distributions so that the observed initial choice is optimal within the model. The subsequent trajectories of wages in all occupations are simulated using our estimates for price changes and skill accumulation, varying the dispersion of the idiosyncratic shocks across experiments. We stick to the four broad occupation groups and draw $100 \times 50{,}000$ careers for each experiment. This balances the ability to summarize the results on the one hand and broadly resembles the effective size of detailed occupations in our application on the other hand. Section C.2 of the Appendix reports on some dimensions of the actual data—occupational switchers, the distribution of wage innovations, and the evolution of wage inequality—that serve as a backdrop for judging what may constitute reasonable values for simulation inputs like, for example, the variance of skill shocks.

In Section C.3, we analyze the performance of our estimation method when the data generating process is precisely the one described in Sections 3.1–3.2. A detailed verbal description is provided at the beginning of C.3; its four subsections contain tables and figures for varying specifications regarding the distribution of the idiosyncratic skill shocks. In order to judge the quality of the approximation (4), we first shut these shocks off altogether. The only randomness in this experiment comes from the initial draws and from the evolving prices at the aggregate level. None of the 4×100 estimated lines is visually discernible from the respective truth; we thus conclude that the approximation of individual wage growth under optimal occupation choice in Equation (4) is unlikely to be causing a bias in our basic setting.

We then set the standard deviation of idiosyncratic skill shocks to half of the standard deviation of innovations to wages in the SIAB. This yields switching behavior,

wage innovations, and an evolution of the wage structure very similar to those in that actual data; we thus term this distribution to have "moderate shocks". As predicted at the end of the previous section, the OLS estimates show a modest upward bias of stayers' skill accumulation coefficients, whereas the IV estimates are almost exactly on target.[15] Both sets of skill price estimates track the evolution of their actual values very closely. Intuitively, mistakes we make with respect to the structural accumulation in the base period cancel out in the estimation period, i.e., in Equation (10) for the OLS. This basic pattern holds true even when tripling the size of the shocks.[16] We overestimate skill accumulation, particularly when using OLS, but skill price estimates remain remarkably close to their targets. Finally, adding persistence to the skill shocks by means of an AR(1)-process does not alter these conclusions either.

One aspect that previous literature has emphasized are fixed costs of switching occupations (e.g., Cortes and Gallipoli, 2017). In our framework, the point of indifference between staying in an occupation and switching will now be determined by wages adjusted for switching costs. This means, however, that unadjusted wages of switchers will exhibit jumps at the indifference point, introducing a potential bias to our estimates. We work this case out theoretically in Section B.3 of the Appendix; Section C.4 presents Monte Carlo analyses examining the bias' importance. First, in a model without skill shocks and with moderate switching costs (5% of annual wages), our approximation (4) continues to work well. OLS estimates recover skill prices and stayers' skill accumulation coefficients almost exactly in such a specification. As previously, we then add moderate and large skill shocks, paired with moderate and high (20% of annual wages) switching costs. All pictures show that the basic conclusions from the corresponding exercises without switching costs remain the same: We slightly overestimate the structural skill accumulation coefficients,[17] but skill prices are estimated with remarkable precision.

[15] Also as expected, the cross-accumulation parameters are generally upward-biased in the OLS; and in the IV with weak instruments, they are large in absolute values.

[16] The descriptives on the resulting data in C.3.3 show that tripling the shocks is clearly an extreme case. There is far more switching in all directions compared to the SIAB, wage growth is twice as high and more dispersed than in the data, and wage inequality is skyrocketing.

[17] As one would expect based on our theoretical analysis, the inertia generated by switching costs leads to a somewhat larger overestimation of the off-diagonal elements of Γ.

Another key extension of our approach is to the generalized Roy model, including non-pecuniary values of occupations in the worker's decision problem (e.g., as in Lee and Wolpin, 2006). Similar to the case with switching costs, workers who move to an occupation with lower (higher) non-pecuniary value will exhibit positive (negative) jumps in wages to compensate for the amenity difference. We show formally in Appendix B.3 that, if the non-pecuniary values are time-constant, the skill accumulation parameter $\hat{\Gamma}_{k',k}$ in our main specification will absorb them. If they are time-changing, the estimation Equation (9) has to be augmented and include regressors for occupation switches ($\Delta I_{k,i,t}$) on top of average occupation choices ($\bar{I}_{k,i,t}$) to control for (and estimate) the respective "wage compensation". Section C.5 of the Monte Carlo analyses examines such a case with rising amenities in one of the occupations, finding that the $\Delta I_{k,i,t}$ correction is indeed necessary but then we recover the skill prices and skill accumulation as well as before (plus the changing amenities themselves).

We also show formally in the Appendix that what we have referred to as idiosyncratic skill shocks is observationally equivalent in our analysis to a basic model of employer learning about workers' skills (e.g., as in Altonji and Pierret, 2001; Gibbons et al., 2005). This is due to the fact that log-linearity allows us to write the model in terms of expected skills, which can evolve because of changes in actual skills (our formulation above) or because employers change their expectations about individuals' skills over time. The two interpretations are not mutually exclusive, of course.

Finally, we examine an alternative panel data approach for estimating skill prices due to Cortes (2016), who uses individual $\times$ occupation specific fixed effects in order to control for skill selection. First, we show theoretically how to generalize Cortes' estimation in order to flexibly control for a rich model of worker skill accumulation. We then implement this approach in the Monte Carlo simulations and find that it performs well in most cases. Exceptions are specifications with a lot of switching (i.e., a large number of occupations K or large skill shocks), when the 'exogenous mobility' assumption of fixed effects approaches discussed in Section 3.2 and Appendix B.4 becomes quantitatively important. We conclude that the generalized version of Cortes' method is a useful alternative when the goal is to estimate low-dimensional skill prices; it seems less suitable for applications that feature a large number of occupations.

4 Skill Prices and Skill Selection

This section first presents the estimation results for our main model. These include the evolution of skill prices, the accumulation of skills over the career, and the relation of prices and occupations' average skills with employment growth. We then dig deeper into the nature of the implied selection effects, showing that the skill differences between marginal workers and those who remain in their occupations drive the strongly negative association of employment growth with average skill changes in an occupation.

Throughout the section, we focus on the OLS results because they allow us to estimate the model for both the 120 detailed occupations and the four broad groups. We describe the IV results for the latter along the way. In our main specification, $X_{i,t-1}$ contains two dummies for age groups 25–34 and 35–44 in $t-1$ and an intercept representing the omitted age group 45–54 (recall from Section 3.2 that these are fully interacted with occupation choices). In the final part of this section, we show that our results are robust to a variety of alternative choices regarding data preparation, sample selection, and estimation specification before connecting our results to the literature using a task-based approach.

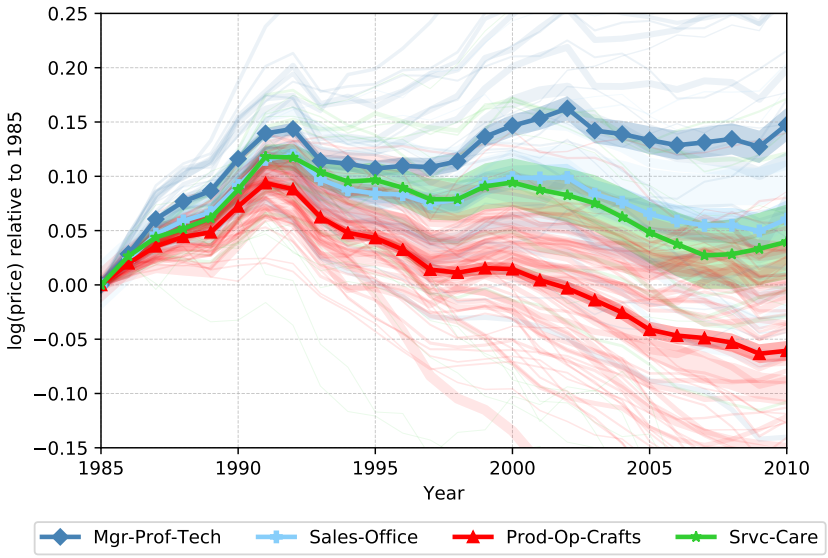
4.1 Estimated Skill Price Changes and Skill Accumulation

Figure 5 depicts the evolution of skill prices, normalizing them to zero in 1985 and cumulating the yearly changes until 2010. In the broad occupation groups, skill prices increased strongly among Mgr-Prof-Tech occupations, modestly among Sales-Office and Srvc-Care; they decreased among Prod-Op-Crafts. The thin lines in the background show that these broad estimates mask substantial heterogeneity among the 120 detailed occupations. We will explore this in greater detail below.

Several distinct periods are noticeable. All prices increased during the favorable economic conditions between 1985 and 1991, although this was already less pronounced for the Prod-Op-Crafts occupations. These have experienced a continuous decline thereafter to the point that prices in 2010 were more than five percent below their initial value in 1985. For the other occupations, there was a drop during the 1992–93 recession as well; prices then stayed constant until they rebounded before the turn of the

century. This rebound was most pronounced for Mgr-Prof-Tech occupations; prices in this group did not change much for the remainder of our sample period. Skill prices fell by about 5 percentage points for Sales-Office and Srvc-Care occupations between 2000 and 2010. All these broad patterns also hold up in the instrumental variable estimates with slightly different numerical values; see Figure D.1 in the Appendix. They are consistent with the job polarization of Figure 1b above; even the temporal changes of employment and skill prices seem to be broadly aligned in the four broad occupations. We will analyze in detail this relationship between employment and price changes, and in Section 4.3 we use tasks measures to approximate the role of RBTC versus other underlying factors for these patterns in the German labor market.

Figure 5: The evolution of skill prices

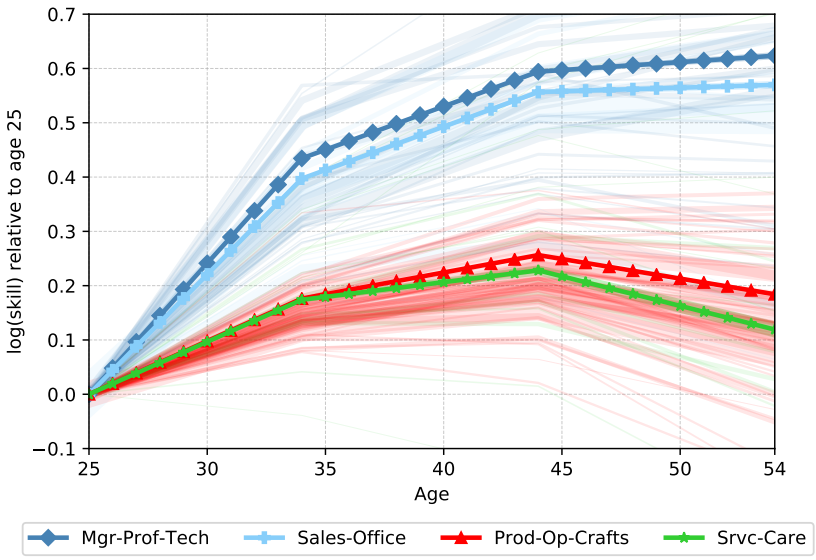


Notes: The figure shows estimated skill price changes. OLS estimates as described by Equation (9). Shaded lines in the background represent the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. The thickness of a shaded background line corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. The shaded areas around the four lines are 95% confidence intervals.

Figure 6 graphs the estimates of the skill accumulation parameters for stayers (i.e., $\Gamma_{k,k}$) in the four broad groups and for the 120 detailed occupations. Skill growth in the early years of the career is steep. Absent changes in skill prices, it implies a 20% growth in wages between age 25 and age 34 for Prod-Op-Crafts or Srvc-Care occupations and 50% or more for the other two. It slows down mid-career and flattens out or turns negative toward the end of prime age. This reflects the well-established concavity of life-cycle wage profiles (e.g., Lagakos et al., 2018). Skill growth differs substantially by

occupation. It is initally very fast in high-earning Mgr-Prof-Tech and Sales-Office occupation groups and never completely ceases. Growth is flatter and eventually peters out or turns negative in the Prod-Op-Crafts and Srvc-Care groups, i.e., occupations that often require physical labor.[18] Again, the broad groups mask substantial heterogeneity across the detailed occupations. At the same time, it is the case that the "blue" occupations on the one hand and the "red and green" occupations on the other hand are almost separate; there are hardly any occupations to be found in the other block. This shows that life-cycle wage profiles are decidedly different across occupations and controlling for this fact is critical in producing reasonable estimates of prices and skills.

Figure 6: Skill accumulation of occupation stayers



Notes: The figure shows estimates for stayers' skill accumulation during the life cycle. OLS estimates as described by Equation (9). Shaded lines in the background represent the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. The thickness of a shaded background line corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. The shaded areas around the four lines are 95% confidence intervals.

Our discussion in Sections 3.3–3.4 has shown that the parameter estimates depicted in Figure 6 may incorporate both the structural coefficients $\Gamma_{k,k}$ and shocks. The reason is dynamic selection: Stayers are more likely to have experienced favorable

[18] One fact to note about the occupations in Germany compared to other countries is that Sales-Office is quite high-earning. Its average wages for men are about halfway between Mgr-Prof-Tech and Prod-Op-Crafts, employment is not declining over time, and we estimate rapid skill accumulation as well as rising skill prices for this occupation group. Using survey data, Cavaglia and Etheridge (2017) also document substantially higher wages for sales and office occupations in Germany than in the U.K.

draws in their occupation,[19] whereas IV estimates should show less such bias. As expected, the IV estimates for the four occupation groups are slightly lower, but none of the broad patterns change. The full set of our $\Gamma_{k',k}$ estimates for the four occupation groups can be found in Section D of the Appendix. The OLS coefficient estimates show that switching into Mgr-Prof-Tech and Sales-Office goes in hand with substantial gains. The magnitude of the off-diagonal elements of Γ suggests that these incorporate sizeable idiosyncratic shocks.[20] The IV estimates for switchers also seem large in absolute value, which is not surprising given that the instruments can only weakly predict who switches out of his occupation. For the purposes of this paper, which requires controlling for, but not predicting, occupation switches, it is perfectly fine to identify the average gains associated with changing occupations. The critical task at hand for the skill accumulation function is to appropriately account for any kind of wage growth that may be due to observables or unobservables changing over the career; the OLS estimates do serve this purpose.

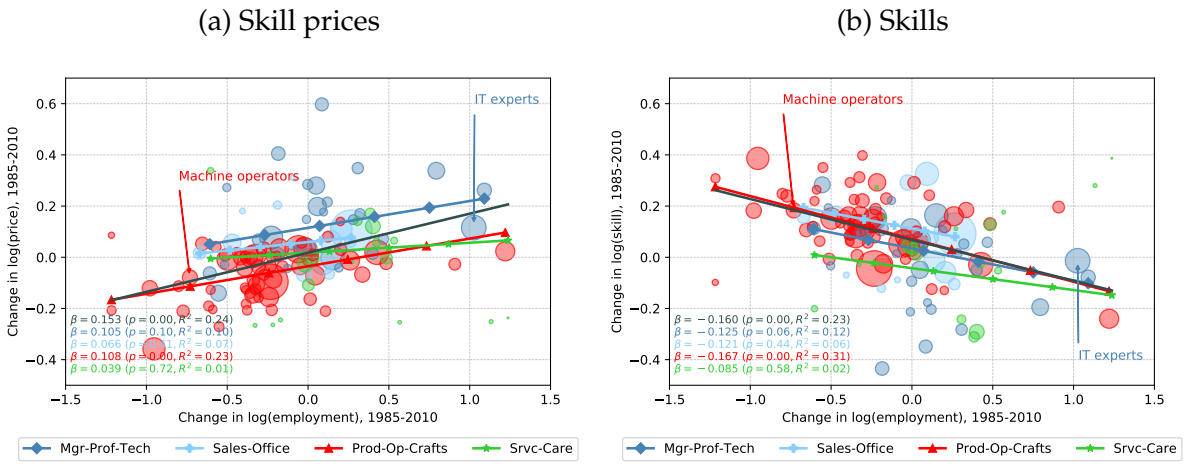
We now hone in on our key finding of this section, namely that employment growth and skill price growth go hand in hand. Figures 1b and 5 show that—consistent with shifts of occupational demand—both employment and skill prices in the broad Mgr-Prof-Tech, Sales-Office, and Srvc-Care groups increased compared to Prod-Op-Crafts. Figure 7a shows that detailed occupations' log employment changes between 1985 and 2010 are positively related to cumulated skill price changes over the same period. The upward-sloping black regression line summarizes this strong relationship for the 120 occupations, which is in marked contrast to the zero correlation for wages not corrected for composition effects (Figure 2a). As shown by the respective sub-regression lines, the relationship also holds within occupation groups. This indicates that our result is more general than a particular demand shifter that predominantly impacts broad occupation groups.

The deviations of the bubbles from the overall regression line can be informative about differences in labor supply to occupations. For example, Mgr-Prof-Tech occupations tend to be located to the right of the graph and above the grand regression line,

[19] As noted before, for the estimation of skill prices this is a core strength of our approach because we allow for endogenous staying as well as switching of occupations.

[20] Judged against the difference between the true values and coefficient estimates in the Monte Carlo experiments of Section 3.4, they are in line with the specifications with "moderate" shocks.

Figure 7: Correlation of changes in employment, skill prices, and skills



Notes: The vertical axis in Panel 7a shows the change in skill prices between 1985 and 2010 estimated with OLS as detailed in Section 3.3. The vertical axis in Panel 7b depicts the change in skills between 1985 and 2010 estimated as the residual between price and wage changes as shown in Equation (11). The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

meaning that prices have grown strongly compared to employment. This pattern is consistent with a combination of positive demand shifts and comparatively inelastic labor supply to those occupations, which seems plausible because of occupational licensing rules and often high educational requirements in Mgr-Prof-Tech. We estimate the largest increase in skill prices for physicians and pharmacists (bubble at the very top of Figure 7a), where educational requirements are high, places in medical school limited, and licensing rules very strict. In contrast, this argument does not apply to IT experts and the corresponding bubble is located below the overall regression line.

It is also possible to find examples where contemporaneous shifts of labor supply and demand seem to be important. For example, the right-most red bubble in Figure 7a are "assistants without further specification". This occupation has arguably experienced a strong positive shock to labor supply, with many low-skilled immigrants and ethnic Germans from Eastern Europe entering it after 1990. At the same time, temporary work agencies substantially increased their demand for this occupation. Taken together, this may generate the pattern that in Figure 7a, these assistants' skill prices remain almost constant while their average skills decline strongly according to Figure 7b. We will not attempt to distinguish different labor supply elasticities from contemporaneous shifts of supply and other factors. These are economic forces that

may generate the variation around the regression line in Figure 7a; its positive slope indicates that demand shifts are the dominant force driving occupational changes.

Figure 7b depicts occupational employment growth against the cumulative changes of average skills implied by the skill price estimates. For every occupation, this is the difference between growth of its average wage (Figure 2a) and its skill price (Figure 7a), i.e., the second term on the right hand side of:

$$\underbrace{\mathrm{E}[w_{i,t}|I_{k,i,t}=1]-\mathrm{E}[w_{i,t-1}|I_{k,i,t-1}=1]}_{\text{Mean wage change}}=\underbrace{\Delta\pi_{k,t}}_{\substack{\text{Price}\\ \text{change}}}+\underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1]}_{\text{Mean skill change}} \tag{11}$$

summed over the years $t = 1985, \ldots, 2010$. The x-axis once more has occupations' growth over the analysis period. Figure 7b thus shows that implied skill changes constitute the flipside of the skill price estimates in the sense that growing occupations' decline of skills is strong. For example, the overall regression line indicates that average skills of the occupations that experience the fastest growth declined by 35 log points on average compared to those that shrank the most. These are large effects; we thus devote the next section to examining their components and their plausibility.

4.2 Accounting for Skill Selection

We have documented in Section 2.2 that entering (leaving) workers' skills on average appear decidedly below those of incumbents (stayers) and that faster-growing occupations draw even less skilled entrants (leavers). Given that growing sectors by definition experience net entry, this could substantially drag down growing occupations' average wages despite rising demand and increasing skill prices. Here we formalize and quantify this effect in the context of our model, showing that it indeed drives the systematic part of the relationship between employment growth and skills.

The change in average skills of an occupation in Equation (11) is determined by three mutually exclusive groups of workers: Those who leave the occupation after period $t-1$; those who stay on after period $t-1$ and are thus incumbent in period t; and those who enter in period t. Denoting the share of leavers in $t-1$ by $p^{lvr}_{k,t-1}$ and the share of period-t entrants by $p^{ent}_{k,t}$, we can decompose the change of average skills

in occupation k into three terms:

$$\underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1]}_{\text{Mean skill change}}=\underbrace{\left(1-\frac{p^{lvr}_{k,t-1}+p^{ent}_{k,t}}{2}\right)\cdot\mathrm{E}[\Delta s^{incumb}_{k,i,t}]}_{\text{1. Skill accumulation of } t-1 \text{ stayers}} \tag{12}$$

$$+\underbrace{\frac{p^{lvr}_{k,t-1}+p^{ent}_{k,t}}{2}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\text{2. Churning: difference entrants in } t\text{, leavers after } t-1}$$

$$+\underbrace{\left(p^{ent}_{k,t}-p^{lvr}_{k,t-1}\right)\cdot\left(\frac{\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{incumb}_{k,i,t}]}{2}+\frac{\mathrm{E}[s^{lvr}_{k,i,t-1}]-\mathrm{E}[s^{sty}_{k,i,t-1}]}{2}\right)}_{\text{3. Marginal selection}}.$$

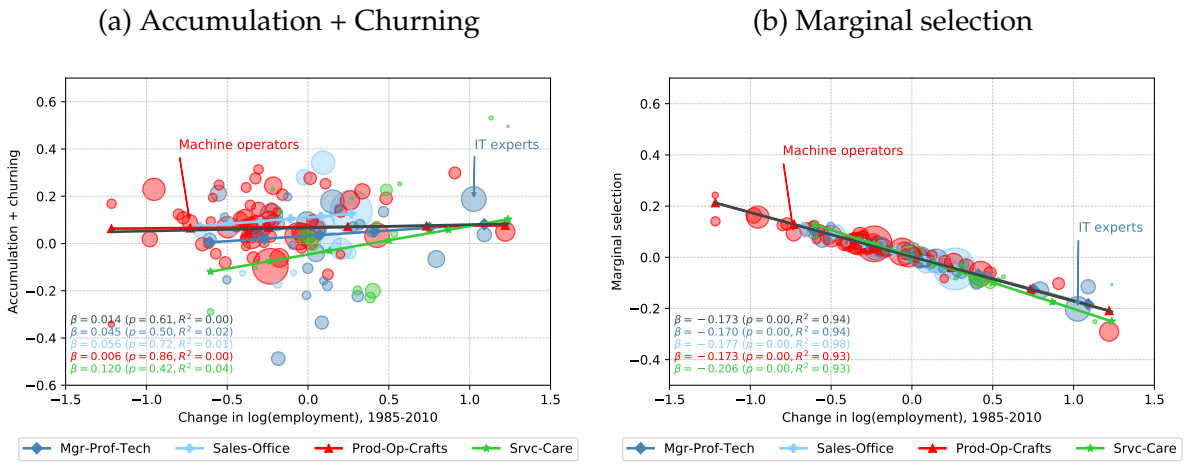
See Section E.1 of the Online Appendix for the steps of the derivation. The first term of Equation (12) reflects the skill accumulation of workers who remain in the occupation. Its impact on occupational skill changes is high if turnover is small and skill accumulation of staying workers is high.[21] The second term is churning, which is composed of average turnover multiplied with the skill differences between period-t entrants and $t-1$ leavers. This will tend to be negative since leavers will have accumulated some skills relative to entrants. It becomes more negative for high turnover occupations and for large estimates of $\Gamma_{k,k}$. Hence, the accumulation and churning effects will often act in opposite directions.[22] Importantly, occupation growth does not have a first order effect on either accumulation or churning. By inducing variation in turnover $\frac{p^{lvr}_{k,t-1}+p^{ent}_{k,t}}{2}$, differences between the numbers of entrants and leavers push terms 1. and 2. in opposite directions.

In contrast, occupation growth directly enters the marginal selection effect in the third term of Equation (12), which is the product of net entry and the difference in skills between marginal and inframarginal workers in an occupation. In fact, since we have documented above in Section 2.2 that, in all occupations, entrants' wages are lower than incumbents' wages and leavers' wages are lower than stayers' wages, occupation

[21] In our setup, it will be generated from the estimated $\hat{\Gamma}_{k,k}$-coefficients and worker demographics.

[22] If an occupation is stable in the sense that employment size and skill composition are constant, they must cancel each other out. The marginal selection effect will be zero because of constant employment and the left-hand-side of (12) will be zero because of constant skills. Skill accumulation of staying workers must equal the churning effect due to the difference in skills between entrants and leavers.

Figure 8: Employment growth vs. the components of skill changes



Notes: Results correspond to sample averages following Equation (12). The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

growth will determine its sign.[23] The marginal selection effect is negative for growing occupations; it is positive for shrinking occupations; and it is zero when there is no change in size. Marginal selection thus formalizes and quantifies the intuition developed in Section 2, whereby the more an occupation grows, the more net entry of less skilled workers it experiences.

Figure 8 plots employment growth against the sum of the accumulation and churning effects (Panel a) and against the marginal selection effect (Panel b). The patterns are strikingly different. Accumulation and churning are much more dispersed and there is no systematic relation with employment growth. The average is significantly above zero. Since the accumulation effect is generally positive and the churning effect generally negative (see Section E.2 of the Appendix for separate plots), this means that the accumulation effect dominates overall. This is not surprising given that the German working age population grew significantly older and more experienced over the period under study.

[23]Note that skill prices are the same for entrants/incumbents in t and for stayers/leavers in $t-1$. Furthermore, both summands in the second term of the marginal selection effect are negative. Hence, knowing wages is enough to determine the sign of this second term; any particular estimate of skills only affects its magnitude.

Figure 8b displays a substantively different pattern. There is a strong negative relationship between employment growth and marginal selection. All 120 occupations are very close to the overall regression line and the four separate regressions are almost on top of each other. This implies that there is no large variation across occupations in the second term of the product in 3., i.e., the sum of the differences between entrants entrants/incumbents and stayers/leavers. However, the absolute level of this term is large and induces strong differences in marginal selection between growing versus shrinking occupations. Considering how Figure 7b is related to its components in Figure 8, marginal selection in the right panel determines the entire negative slope between skill changes and employment changes. The location of the regression line and the variation around it stem from accumulation and churning in the left panel. Therefore, the systematic part of the large selection effects we found in Section 4.1 can be traced back to changes in occupations' sizes multiplied with the (negative) skill differences between marginal and inframarginal workers.[24]

The marginal selection effect lends itself to further analysis. We can split it up into the contributions at entry on the one hand and when leaving the occupation on the other hand. Doing so reveals that the slopes of the regression lines in Figure 8b are made up of steeper slopes for entrants versus incumbents and flatter slopes for leavers versus stayers in the three growing occupation groups; they are the same for the shrinking Prod-Op-Crafts (see Appendix E.2). This might not be surprising given that skills should be lower at occupation entry and that leavers should have a larger impact in shrinking occupations. Digging deeper into this, Tables 1 and 2 decompose the marginal selection effects in two different ways, using the four broad groups for ease of exposition. See Appendix E.3 for the decomposition formulas.

Table 1 breaks down the contributions to marginal selection for the broad occupation groups by the origin or destination of marginal workers. Maybe not surprisingly, the single largest contributor are labor market entrants, who make up at least 35% of the total for the three growing occupations and almost one fourth for Prod-Op-Crafts. The main reason for this is that new labor market entrants are a substantial share of

[24] In Hsieh et al. (forthcoming), increasing wages per efficiency unit of skill in an occupation also attract workers of lower quality. Their modeling setup equates overall selection effects with marginal selection. With Fréchet as a specific multidimensional skill distribution, Hsieh et al.'s setup implies that selection just offsets the increasing wages per efficiency unit. Interestingly, this implication is approximately borne out in our approach, which does not make a distributional assumption.

entrants into growing occupations and that they have not accumulated much skills in the respective occupation yet. In general, there are some striking differences between the three growing occupation groups on the one hand and Prod-Op-Crafts on the other hand. For the latter, switches to and from unemployment are particularly important. They make up almost 50%; the effect on average skills is positive because of net outflows. Entrants from unemployment account for the same share of marginal selection in Prod-Op-Crafts as sample entrants. In contrast, the combined contribution of unemployment is around 20% for the oter three occupation groups and it negatively affects average skills because of net inflows. Leavers to outside of the labor force have a fairly large effect everywhere, that is, a substantial amount of less-skilled workers are leaving all occupation groups in each period. However, entrants from outside the labor force exert a counteracting effect on marginal selection for the growing occupation groups; they often enter from other forms of employment that are not covered in our data (self-employment, civil servants, work abroad) and they are quite high-skilled compared to incumbents. Leavers after age 54 also mostly exert a counteracting effect as they have accumulated substantial skills over their careers and they exit our sample for exogenous reasons.

Quantitatively, most of the marginal selection effect in Table 1 is accounted for by moves into or out of unemployment, the labor market, or the sample.[25] Nonetheless, direct switches between occupations are non-negligible and of economic interest because they almost always positively contribute to marginal selection. That is, entrants into an occupation, independent of the origin occupation, are less skilled than the incumbents. Leavers from an occupation, independent of the destination occupation, are less skilled than the stayers. The partial exception is Mgr-Prof-Tech, where switchers from that occupation group are more skilled than the incumbents in their destination and switchers into Mgr-Prof-Tech tend to be more skilled than the stayers in the respective origin occupations.[26] But overall this evidence once again indicates that, at the time of switching, incumbents and stayers have strong specific skills in their occupa-

[25]The lion's share of these moves is part of transitioning between jobs. In Online Appendix F.1 we repeat Table 1 for our sample where we have filled non-employment spells using the wage and occupation of the adjacent spell with the lower wage. We find that the role of switches between occupations approximately doubles (there are still permanent entry and exit from the sample as alternative contributors). We will come back to this and the robustness of our results in Section 4.3.

[26]The latter makes sense as, e.g., promotions to team leader might yield such a change of occupation.

Table 1: Contributions to marginal selection by origin and destination activities

		Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Entrants	Switchers from Mgr-Prof-Tech		-0.05	-0.00	-0.00
	Switchers from Sales-Office	0.01		0.01	0.01
	Switchers from Prod-Op-Crafts	0.13	0.11		0.07
	Switchers from Srvc-Care	0.01	0.02	0.02	
	From unemployment	0.11	0.10	0.22	0.11
	From outside of the labor force	-0.01	-0.02	0.09	-0.04
	Sample entrants	0.38	0.48	0.23	0.35
Leavers	Switchers to Mgr-Prof-Tech		-0.05	-0.01	0.00
	Switchers to Sales-Office	0.05		0.01	0.02
	Switchers to Prod-Op-Crafts	0.10	0.14		0.15
	Switchers to Srvc-Care	0.02	0.03	0.01	
	To unemployment	0.07	0.07	0.26	0.11
	To outside of the labor force	0.20	0.21	0.15	0.23
	Sample leavers after age 54	-0.06	-0.04	-0.01	0.01

Notes: The numbers represent relative contributions to the marginal selection effect within each broad occupation group during 1985–2010. Columns sum to one. The actual sizes of the effects are -0.03 (Mgr-Prof-Tech), -0.02 (Sales-Office), 0.06 (Prod-Op-Crafts), and -0.04 (Srvc-Care). The explicit decomposition formulas are in Appendix E.3.

tion compared to marginal workers, which is hard to reconcile with a one-dimensional ranking of occupations by skill. Online Appendix B.2 rejects the one-dimensional skill model in our data based on this type of evidence.

Table 2 shows the contributions to marginal selection by the sources of workers' skills. We employ the longitudinal information in the data to separate workers' skill endowment at the most recent entry into the occupation from their skill accumulation since then. In particular, we calculate the endowment from observed wages and normalized prices at the time of entry. We then obtain predicted skill accumulation during the current stint by summing the respective estimated $\hat{\Gamma}_{k,k}$ over the worker's tenure. Finally, we calculate the deviation of workers' actual wages from our prediction based on systematic skill and price changes. The first row in Table 2's top panel shows that in all occupation groups, entrants have lower skill endowments than incumbents had at the time that they were entrants. The corresponding bottom panel shows that also

Table 2: Contributions to marginal selection by source of skills

		Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Entrants	**Endowment** at the most recent entry into the occupation group	0.14	0.16	0.21	0.33
	Predicted **skill accumulation** since the most recent entry	0.40	0.41	0.24	0.08
	Deviation of skills from the prediction since the most recent entry	0.10	0.07	0.13	0.08
Leavers	**Endowment** at the most recent entry into the occupation group	0.08	0.06	0.18	0.35
	Predicted **skill accumulation** since the most recent entry	0.16	0.19	0.04	0.09
	Deviation of skills from the prediction since the most recent entry	0.13	0.11	0.20	0.08

Notes: The numbers represent relative contributions to the marginal selection effect within each broad occupation group during 1985–2010. Columns sum to one. The actual sizes of the effects are -0.03 (Mgr-Prof-Tech), -0.02 (Sales-Office), 0.06 (Prod-Op-Crafts), and -0.04 (Srvc-Care). The explicit decomposition formulas are in Appendix E.3.

leavers are negatively selected relative to stayers when comparing endowments retrospectively.[27] The resulting contribution to marginal selection that is due to different skill endowments is substantial, ranging from one fifth in Mgr-Prof-Tech and Sales-Office to two thirds in Srvc-Care. Endowments at entry into the occupation can be interpreted as a "classic selection effect", i.e., as in cross-sectional models where workers' skill endowments are drawn before making the occupational choice.

Workers' skills do however change during their stint in an occupation and this has important separate effects on marginal selection. Table 2 shows that for the high-accumulation Mgr-Prof-Tech and Sales-Office occupations, around 40% of marginal selection is due to skills accumulated by incumbents (accumulation for entrants is zero by construction).[28] Another 15–20% percent is due to more skills accumulated by stayers compared to leavers (i.e., stayers' tenure is on average longer than that of leavers). Not surprisingly, the magnitude due to skill accumulation is very heterogeneous and

[27] Comparing endowments in Table 2 presents a model-consistent way to control for experience in Figure 3 above. Also by this measure, both entrants or leavers earn less than incumbents or stayers.

[28] Notice that, while the skill differences due to skill accumulation are in principle temporary, higher values for incumbents will continue to contribute towards the marginal selection effect as long as the respective occupation keeps growing and drawing in new, less skilled workers.

it accounts for less than 30% of the marginal selection effect in Prod-Op-Crafts and for even less in Srvc-Care. This heterogeneity underlines the importance of flexibly modeling skill accumulation across occupations: In a model with homogeneous returns to experience the effect would only depend on tenure and entry age, which vary much less across occupations and may even lead to inverse predictions such as overall accumulation being highest in Prod-Op-Crafts.[29]

The final contributor to marginal selection in Table 2 are deviations from what is already captured in our estimates $\hat{\Gamma}_{k,k}$. These deviations are due to systematically different skill shocks of incumbents/stayers compared to entrants/leavers during the stint.[30] Again, the value is zero by construction for entrants, showing that incumbents are positively selected on this margin as well. The same holds true for stayers versus leavers. The effects are quantitatively substantial and economically interesting. They show that the argument we made in Section 3—that staying in an occupation is endogenous in the sense that only workers who receive sufficiently favorable skill shocks will decide to remain in it—is not merely an academic one. The deviations are consistent with learning models of occupational mobility, such as Groes et al. (2014) and Papageorgiou (2014), which show that workers who leave an occupation previously systematically deviate from their peers in terms of wages (expected skills). While predicted skill accumulation is quantitatively large, stayers in occupations are clearly selected according to their idiosyncratic skill shocks. This underscores the importance of the self-selection model underlying our estimation method.[31]

To sum up the evidence from this section, marginal selection can account for the systematic part of the relationship between skill changes and employment changes across occupations implied by our estimates, both qualitatively and quantitatively.

[29] In our data, Prod-Op-Crafts occupations exhibit the longest average tenure (more than 14 years), Srvc-Care the shortest (10 years), and the other two are right in the middle (just below 12 years). Abstracting from differences in entry age, the skill accumulation effect on marginal selection would be highest for Prod-Op-Crafts. In contrast, the longer average tenure does not translate into a quantitatively large effect in our model because the skill accumulation coefficients are much lower for Prod-Op-Crafts than for Mgr-Prof-Tech or Sales-Office (see Figure 6).

[30] As discussed in Section 3.4, differential employer learning about skills is an alternative explanation.

[31] This is a case where the more general acceleration or deceleration interpretation of skill price changes from Section 3.3 matters. In particular, if skill prices had already risen in the base period, we would overestimate the difference in skill accumulation of entrants versus incumbents (and leavers versus stayers), while underestimating the difference in endowments at the most recent entry. The (economically instructive) role of deviations from the model prediction is unaffected by this more general interpretation, however. See Online Appendix E.3 for more details.

This selection effect fundamentally stems from the fact that entrants and leavers are substantially less skilled than incumbents or stayers in any occupation; it is *due to* sector growth. Marginal selection also conforms with reasonable economic notions of the underlying selection effects. First, a large part of it are moves into and out of employment. Second, most almost all groups of switchers contribute negatively (positively) to skills changes in the destination (origin) occupation. The skill differences of marginal versus inframarginal workers consist of differing endowments at entry, skill accumulation of incumbents, and endogenous switching (staying) of those workers who experience negative (positive) shocks during their stint in an occupation. These effects are strong and seem economically plausible. As their magnitude does not depend much on our skill price estimates, we consider the results in this section separate and substantive evidence in favor of the results from our estimation method.

4.3 Robustness of Results and the Task Content of Occupations

Appendix F examines the robustness of our empirical results in alternative samples and estimation specifications. We briefly summarize the reasons for and results of these robustness checks in the following. Finally, we connect to prior literature by describing occupations via the task content of work.

Filling non-employment spells: In our view, a key robustness check is to allow for endogenous unemployment and exit from the labor force. For instance, when the skill price in an occupation declines, workers might prefer to temporarily leave employment over switching to another occupation directly if the benefits they obtain in unemployment are sufficiently high. As an alternative, we therefore include all intermittent non-employment spells in our sample by imputing workers' wages and their occupation choices. We do this by comparing wages before and after the non-employment spell, and assign workers the lower of those two wages adjusted for inflation as well as the corresponding occupation. That is, we assume that workers could well have worked in the lower paying occupation but decided to become unemployed or exit the labor force for some time instead.

Re-running the entire analysis on the sample constructed in this way, we find that the estimated skill accumulation coefficients are generally smaller and they turn neg-

ative in cases that one would expect to be "downward" switches (e.g., from Mgr-Prof-Tech to Prod-Op-Crafts). Yet the other results are similar to before: The correlation between wage and employment growth is approximately zero but it is strongly positive between price and employment growth (though slightly flatter than in the main sample). In addition, the implied skill changes are again negative and closely related to marginal selection. Section 5 returns to this filled sample for some of the wage inequality analyses.

Different demographic groups: We have restricted our main sample to prime age West German men as these can be defined consistently over the 1975–2010 period and many potentially confounding factors (e.g., rising participation and education rates, changing discrimination) do not apply. Nonetheless, it is still informative to see whether the broad results hold up when we change the demographics. First, in a wide definition that adds women, East Germans, and workers who are always foreigners, the results are very similar to our main sample.[32] If we consider West German women only, it is striking that the employment distribution is very different, with substantially more Sales-Office and Srvc-Care occupations (indicated by the bubbles sizes in the respective graphs). Nonetheless, the results for the women sample are similar to our main results: there is no relationship of employment with wage growth but with skill price growth (even slightly stronger), while implied skill changes and marginal selection again point in the same direction. Finally, restricting ourselves once more to West German men, but extending the age range to 20–60, our original findings are confirmed with somewhat steeper slopes. This makes sense as very young workers had less time to accumulate skills on their jobs and early retirement—which was important over many of the years in our sample period—was likely to be selective.

Different estimation specifications: We also estimate different model specifications that were discussed in Section 3. First, we employ the identification approach pioneered by Heckman et al. (1998), which assumes that mature workers' skill growth should be rather flat. Our estimated coefficients depicted in Figure 6 lend support to this assumption. At the same time, possibly forward-looking choices—i.e., via pick-

[32]The same holds if we conversely exclude anyone who was ever coded as a foreigner; naturalized citizens who change their foreigner status are discussed further in Section 5.

ing occupations with high skill accumulation—should be less of a concern in this age group. We thus follow Heckman et al. (1998)'s flat spot approach and set skill accumulation to zero for the 45–54 year old subsample. This obtains a similarly steep relationship between skill price and employment changes as in the baseline estimation. Marginal selection also works in the same direction as the implied skill changes, although it is somewhat flatter.

We then return to our main sample and enrich the skill accumulation function to be education-group specific. The results hardly change compared to the baseline where occupational skill accumulation differs only across age-groups. Next, we allow for changing non-pecuniary amenities in occupations by augmenting the estimation equation with regressors for occupation switches (detailed derivation in Appendix B.3). We perform this exercise for the four broad occupations only because of the extensive data requirements. Similar to Hsieh et al. (forthcoming), we find that changing amenities (or, alternatively, changing preferences) hardly have an effect on the estimated changes of skill prices.[33] We also estimate the alternative occupation-specific fixed effect approach by Cortes (2016). The relationship between employment and price changes is somewhat flatter than in our proposed method but still highly significant.

Notably, in each of the different samples and estimation specifications the relationship between occupational wage and employment growth is essentially flat, whereas estimated skill prices and employment growth correlate positively. This indicates that demand shifts were dominant across broader demographic groups and that selection effects are generally strong, masking this underlying driving force. Moreover, we find that the estimated price changes positively correlate across samples and estimation specifications, and that implied skills and marginal selection work in the same direction throughout.

Connecting to the task-based approach Finally, we connect to a large literature that has investigated occupational changes with the task-based approach (e.g., Autor et al.,

[33] Hsieh et al. (forthcoming) introduce a general equilibrium Roy model in which workers sort on either (unobserved) talent or preferences. They report a small, weakly positive correlation between occupational employment and earnings growth similar to Figure 2a above (Figure 10, p. 41 Hsieh et al., forthcoming). Based on that finding in combination with their model prediction, they conclude that workers primarily sort into occupations based on talent as opposed to preferences.

2003; Firpo et al., 2013; Yamaguchi, 2018). For Germany, several authors have used the Qualifications and Career Surveys (QCS) to measure routine versus non-routine task content in particular (e.g., Spitz-Oener, 2006; Antonczyk et al., 2009; Gathmann and Schönberg, 2010). In the last section of Appendix F, we also employ the QCS to construct routine as well as analytical, interactive, and manual task content for our 120 occupations. We then relate these measures to employment growth, wage changes, and our estimates for prices and skills.

The resulting graphs show that occupations intensive in analytical (often in the Mgr-Prof-Tech group) and interactive (Mgr-Prof-Tech and Sales-Office) tasks indeed grew quite strongly, whereas employment in routine-intensive (Prod-Op-Crafts) occupations declined. High analytical and interactive task content of occupations helps predict rising wages. However, the relation with estimated skill prices is even steeper. Conversely, implied skills deteriorate in analytical and interactive task content. The correlation between routine task intensity and average wages is zero; this is composed of falling prices and rising skills. All this is consistent with the impact of RBTC on these occupations and with our finding that skill price changes are counteracted by selection effects.

The case of manual-task intensive occupations (mostly in the Prod-Op-Crafts and Srvc-Care groups) is also in line with the latter general finding. But it seems that the overall demand shift was negative because employment as well as average wages and skill prices declined. One likely reason for this is measurement, since the QCS questionnaires have some difficulty distinguishing between routine and manual job tasks. The other is that alternative demand forces than RBTC have lifted the employment and skill prices of Srvc-Care occupations, despite their high (measure of) manual tasks.[34]

These results demonstrate the usefulness of task measures as a dimension-reduction device, particularly when working with more limited datasets. It is especially helpful to study specific drivers of occupational change. At the same time, using detailed oc-

[34] Additional forces that could have worked on Srvc-Care include demand for social skills or consumption of low-skill services (Deming, 2017; Autor and Dorn, 2013; Mazzolari and Ragusa, 2013). In the case of Prod-Op-Crafts occupations, employment may have declined even more than predicted by RBTC because of trade and offshoring (Autor et al., 2013; Goos et al., 2014). See also Footnote 2.

cupations directly is most flexible and does not require precise measurements of all task dimensions for which demand may have changed.[35]

5 Skill Prices and Wage Inequality

We have shown that selection effects largely explain why occupational wages and employment growth are uncorrelated over the period under study. By a similar token, selection may shroud the relation between demand shifts and wage inequality, particularly between occupations. In this section, we thus examine to what extent selection may also be responsible for the result that occupations exhibit limited explanatory power for the increase of wage inequality. Running Mincer-regressions, Card et al. (2013) obtain only small decreases in residual wage inequality when adding occupation dummies. Dustmann et al. (2009) find that in the lower half of the wage distribution, occupational demand is not a first-order factor driving wage differences. We first use only the estimated skill prices and selection to quantify the forces driving between-occupation inequality. We then employ the full version of our model to disentangle the components that affect various percentiles of the wage distribution,[36] paying particular attention to entry wages, demographics, skill accumulation, and prices.

5.1 The Attenuating Effect of Selection On Inequality

Over the period of our study, the variance of log wages multiplied with 100 went up by 12.4 points from a baseline of 14.3. The component due to differences between occupations started at a value of 5 in 1985. It then more than doubled and reached almost 40% of the overall inequality in 2010. A substantial share of the increase thus occurred between occupations, consistent with occupational demand (e.g., due to routine-biased technical change and offshoring as in Acemoglu and Autor, 2011) but also with other factors having been important drivers of wage inequality.

[35] For example, Firpo et al. (2013), Blinder and Krueger (2013), and Goos et al. (2014) construct task measures for offshorability in the U.S. and Europe. Deming (2017) constructs measures of social skills.

[36] Due to the nature of our data, we restrict attention to wage inequality as opposed to overall inequality. It is thus important to note that we do not see a clear trend in labor force participation rates of German men over most of the period under study. In particular, there was a decline between 1975 and 1989, but rates stabilized around 93-94% thereafter. This is in stark contrast to U.S. men, where rates dropped from almost 94% to below 90% between 1989 and 2010.

In particular, one question that several papers before us have asked is whether changes in the demographic structure of the population were such a factor. The first column of Table 3 reports on a counterfactual analysis similar in spirit to that of Figure 16 in Autor (2019).[37] Holding wages at their 1985 level, we reweight observations with the distribution of age, foreigner status, and education in 2010.[38] This exercise answers the question: what if choices conditional on these observables and wages were constant at their 1985 levels, but the demographic structure had shifted to that of 2010 (due to population aging, increased immigration, and rising educational achievements of younger cohorts)? Quantitatively, the answer is similar to that of Autor (2019) in that the effects make up something like a fifth of the total increase and a third of the increase in between-inequality.

Table 3: Decomposition of the between-variance of wages, data and counterfactuals

		Counterfactuals			**Actual**
		Rewgt. age, foreign, educ.	Prices only	Prices + rewgt. age, foreign, educ.	Data + price estimates
Overall $\Delta\sigma^2(w_{i,t})$		2.41	5.13	9.56	12.41
Between $\Delta\sigma^2(\bar{w}_{k,t})$		1.74	5.13	8.88	5.25
$2 \cdot \sigma(\Delta\bar{w}_{k,t}, \bar{w}_{k,1985})$	$2 \cdot \sigma(\Delta\pi_{k,t}, \bar{w}_{k,1985})$	0.00	3.23	3.23	3.23
	$2 \cdot \sigma(\Delta\bar{s}_{k,t}, \bar{w}_{k,1985})$	0.53	0.00	0.53	-0.53
$\sigma^2(\Delta\bar{w}_{k,t})$	$\sigma^2(\Delta\pi_{k,t})$	0.00	1.89	2.36	1.76
	$\sigma^2(\Delta\bar{s}_{k,t})$	1.21	0.00	1.21	3.02
	$2 \cdot \sigma(\Delta\pi_{k,t}, \Delta\bar{s}_{k,t})$	0.00	0.00	1.55	-2.24

Notes: All values are multiplied with 100. The levels in 1985 are 14.3 (overall) and 5.0 (between). Based on specification with 120 occupations. $\bar{w}_{k,t}$ refers to the average wage in occupation k in year t. The counterfactual experiments are: *Rewgt. age, foreign, educ.*: take observations in 1985 and reweight them to match the 2010 distribution of these characteristics with weights computed following DiNardo et al. (1996) in order to obtain 2010 wages. *Prices only*: take individual wages in 1985 and add our estimated price changes to obtain 2010 wages. *Rewgt. age, foreign, educ. + prices*: Combine both experiments.

With the help of our model we can gain further insights into the components that have driven changes of between inequality. Denoting average wages (skills) in an oc-

[37] The closest to his analysis includes occupational choices among the variables used for reweighting. The results of this exercise can be found in Appendix G.1. They are quantitatively similar to our specification in Table 3. We prefer this specification because age, foreign, and education are arguably all factors that mostly contribute to occupational supply as opposed to demand.

[38] To compute the weights, we follow DiNardo et al. (1996) using a logit model with 30 dummies for detailed ages between 25–54, a dummy for being permanently German or not, as well as three dummies for education status.

cupation by $\bar{w}_k$ ($\bar{s}_k$), we can write the change between 1985 and 2010 as:

$$\begin{aligned}\Delta\sigma^2(\bar{w}_{k,t}) = &\underbrace{2\cdot\sigma(\Delta\pi_{k,t},\bar{w}_{k,1985}) + 2\cdot\sigma(\Delta\bar{s}_{k,t},\bar{w}_{k,1985})}_{2\cdot\sigma(\Delta\bar{w}_{k,t},\bar{w}_{k,1985})} \\ &+ \underbrace{\sigma^2(\Delta\pi_{k,t}) + \sigma^2(\Delta\bar{s}_{k,t}) + 2\cdot\sigma(\Delta\pi_{k,t},\Delta\bar{s}_{k,t})}_{\sigma^2(\Delta\bar{w}_{k,t})}\end{aligned} \tag{13}$$

See Appendix G.1 for the detailed derivation. First consider the terms underneath the braces, which involve only wages. They say that if overall wage inequality was constant $\Delta\sigma^2(\bar{w}_{k,t}) = 0$ and there were any changes in the wage structure across occupations $\sigma^2(\Delta\bar{w}_{k,t}) > 0$, it must be that occupations at the bottom of the distribution experienced better wage growth than those at the top on average $\sigma(\Delta\bar{w}_{k,t},\bar{w}_{k,1985}) < 0$. Using our model, the main terms in (13) now break these two components into changes of prices and changes of skills. We start by applying this decomposition to various counterfactual experiments in order to better understand the mechanisms at work.

The remainder of the first column of Table 3 shows that the reweighting procedure only affects skills; all terms involving price changes are zero. The covariance of skill changes with baseline wage levels is positive. This is a reflection of the fact that the population grew older and more educated together with high-wage, high-education occupations (Mgr-Prof-Tech, Sales-Office) featuring faster skill accumulation over the life cycle. However, while we will show below that these changes in the demographic structure had an important role for overall inequality, they play a limited role for explaining between-occupation inequality. Including occupations among the variables used for reweighting does not change these conclusions (see Appendix G.1).

The second column of Table 3 reports on the results from the opposite experiment, which isolates the effect of price changes. Holding constant the 1985 demographic structure and occupation choices, we add the cumulative changes of occupational skill prices between 2010 and 1985 to individuals' wages. These effects alone generate almost the entire increase of between inequality. The bulk of the effect stems from the covariance between price changes and initial wage levels. Prices rose in Mgr-Prof-Tech, Sales-Office, and Srvc-Care occupations; the first two featured high wages already in 1985 and employment there is much larger than in Srvc-Care. Our preferred interpretation of this term is that it reflects the nature of demand shifts: during the period

under study, they happened to benefit high-wage occupations more. Naturally, any term involving skill changes is zero.

The third column shows what happens if both experiments are turned on. The variance of price changes rises somewhat due to the different weights; all other effects from the separate experiments remain the same. The covariance between price and skill changes is substantial and positive. Overall, this counterfactual overestimates the rise of between inequality by two thirds. Looking at the first line only, one may even be tempted to think that this exercise explains a large share of the overall rise in inequality (77 %).

However, a comparison with the last column, the actual between variance and its components, reveals that this large "explained" share is far off, since there are important dampening effects of selection on wage inequality. In particular, the economic mechanism described at length in the previous section—a deterioration of skills in occupations where prices rose—has a strong impact on inequality. This strong negative covariance is everything but mechanical: if we interpret price changes as mainly driven by demand shifts and the demographic changes captured by the reweighting as supply shifts to occupations, the third column of Table 3 suggests that these shifts covaried positively. The impact of -2.24 points in the actual data as well as the negative covariance of skill changes and initial wage levels are therefore important attenuating selection effects. As a result, the actual contribution of skill changes to between inequality is negligible whereas in the counterfactual it is $+3.29$ points overall.

What we have just described is consistent with theoretical results by Heckman and Honoré (1990) for a two-sector Roy economy. They showed that, if the population distribution of skills is log concave, self-selection in the Roy model will generally lead to more equal wages compared to random assignment into occupations. With respect to the particular case at hand, when the correlation of skills in the different occupations is sufficiently low, average skills in the occupation with declining prices will unambiguously improve and they will unambiguously deteriorate in the occupation with rising prices.

Our results show why decompositions based on observables alone have difficulties generating quantitatively meaningful increases of inequality: so long as average wages across occupations are more or less constant (e.g., see again Figure 2), changing demo-

graphics and even large shifts of the employment structure across occupations exert limited impact. The reason is that underlying skill prices and supply changes, which would have raised between-occupation inequality further than what is observed, are counteracted by strong selection effects.

5.2 Factors Contributing to Wage Inequality

While the economic forces under scrutiny in this paper are most important for inequality between occupations, our model can be employed to gain a better understanding of the overall development of the wage distribution, too. In the following, we use our estimates to disentangle the factors that contributed to differences between the quantiles of the wage distribution.

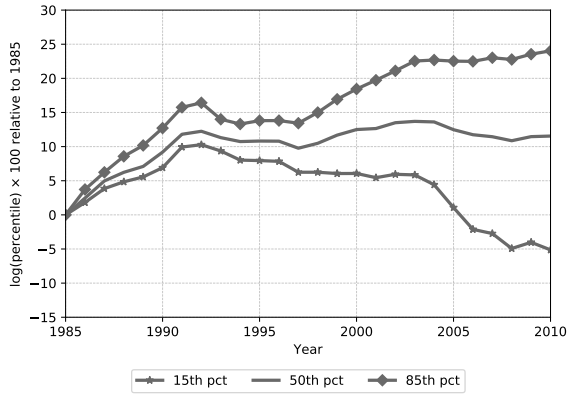
Figure 9 plots the evolution of the percentiles of the wage distribution in the data and in various scenarios based on our model. Figure 9a just repeats Figure 1a for ease of comparison; it shows the strong widening of the German wage distribution (Dustmann et al., 2009; Card et al., 2013). Figure 9b plots the individual-level predictions from our model. In order to obtain an individual's predicted wage in a particular year, we start from the initial wage observed in our data[39] and follow his occupational choices over the life-cycle, adding the relevant skill accumulation parameters and skill price estimates along the way. The predictions track the data closely, both qualitatively and quantitatively. Note that all percentiles in all panels are normalized to zero in 1985; Table G.2 in the Appendix shows that our model is close to its targets also for the levels of these percentiles and the variance.

The remaining panels of Figure 9 investigate the drivers of the model prediction by starting with the most basic version and turning on our model's features one after the other. Panel c reports on how the three percentiles would have evolved if workers had kept their initial wages for their entire working life. Many variants of supply changes would directly affect this scenario. For example, one may expect the expansion of tertiary education to lead to higher entry wages for the additional university graduates, raising the upper percentiles. The results show that the median and the 85th percent-

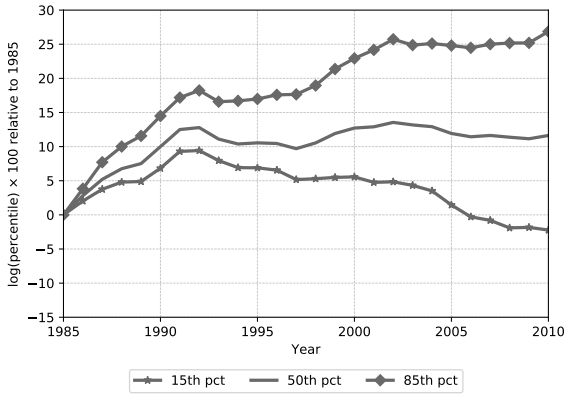
[39] For workers who may have entered the labor market before our sampling period starts—i.e., those born before 1950 observed to be working in 1975—we use our skill accumulation estimates to impute their initial wages at age 25, assuming they stayed in the same occupation all along.

Figure 9: Wage inequality scenarios

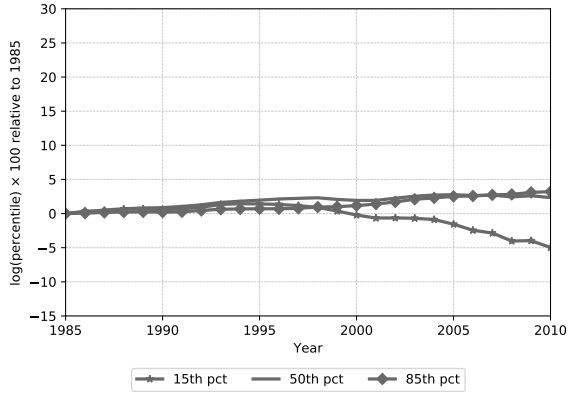
(a) Observed



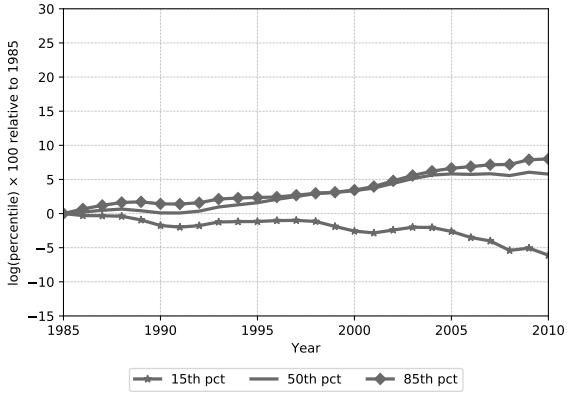
(b) Model



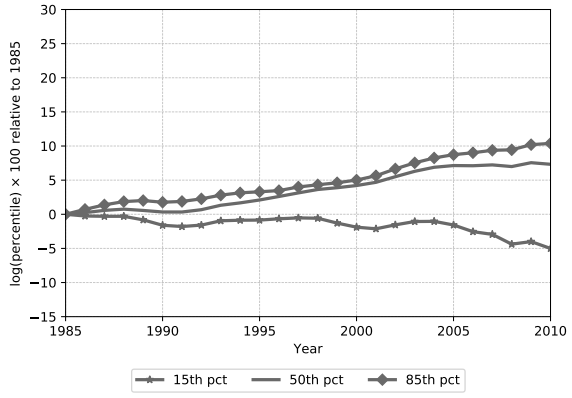
(c) Initial occupation and wage throughout



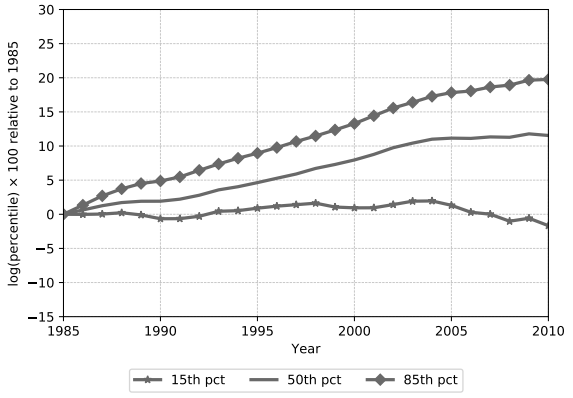
(d) Initial occupation + skill accumulation



(e) Observed occ. + skill acc.; $\Delta s_{k,l} = 0$



(f) Observed occ. + skill accumulation



Notes: Panel a: observed wages. *Panel b*: simulated life-cycle trajectories based on our full model: starting from the initial wage and occupational choice, add all skill accumulation and price change estimates using occupational choices observed in the data. *Panel c*: workers keep their initial wage throughout the life cycle. *Panel d*: workers stay in their initial job throughout the life-cycle; in each period, we add the skills they would have accumulated in that job (i.e., $\Delta s_{k_0,k_0,t}$). *Panel e*: use observed switches, setting direct gains from switching to zero, i.e., $\Delta s_{k,l} = 0 \; \forall \; k \neq l$. Price changes are zero as well, so the difference to Panel d comes purely from differential skill accumulation in occupations. *Panel f*: as in Panel e, but adding the direct gains from switching. The only difference to the full model in Panel b are the price changes, which continue to be zero. In all scenarios, we treat unemployment or out-of-the-labor force spells as follows: when such a spell is observed in the data, simulated workers do not enter the inequality statistics. Furthermore, we assume no depreciation and upon re-entry into paid work add—where relevant—the $\Delta s_{k,l,t}$ with l being the occupation before the spell.

ile rose somewhat. Quantitatively, this is not very important, making up between one fifth (median) and one eighth (85th percentile) of the total increase. All three percentiles evolve rather smoothly, the distinct temporal pattern over time visible in Panels a and b thus does not seem to be driven by changing conditions at labor market entry.

After a small initial increase, the 15th percentile exhibits a pronounced decline starting in the mid-nineties. In fact, this decline is so strong that it could explain the drop of that percentile between 2010 and 1985.[40] This large drop seems due to temporary workers[41] and naturalized citizens, both of whom are frequently the same. Excluding workers ever coded as foreigners from our sample reduces the fifteenth percentile drop by more than two thirds both in Panels b and c (see Figure G.1 in the Appendix). This is consistent with Dustmann et al. (2009)'s hypothesis that, from the 1990s onward, many low-skilled immigrants and ethnic Germans from Eastern Europe increasingly flowed into the West German labor market, worsening the composition of employment at the lower end.

In Figure 9d, we continue to assign workers to their initial occupation, now adding the skill accumulation coefficients. There is hardly any change for the fifteenth percentile compared to Panel c, but the median and 85th percentile rise strongly. The incremental changes are 4 points at the median and 5 points at the 85th percentile, amounting to one half (one third) of the overall changes between 2010 and 1985. Again, all changes happen rather smoothly. The scenario shows that the demographic and occupational composition has a quantitatively strong impact on the rise of the upper half of the wage distribution.

We add the empirically observed switches to careers in Figure 9e, but do not turn on the direct gains from switching, i.e., we set $\Delta s_{k,l} = 0 \; \forall \; k \neq l$. This exercise drives up the median and 85th percentile by an additional three points; it hardly affects the fifteenth percentile. The results show that switches from occupations with flatter age profiles to those with steeper age profiles do matter even if one ignores the oftentimes

[40] Again, the temporal pattern is far off. One would reach a radically different conclusion regarding the fit if one were to compare, say, 1991 and 1985.

[41] We identify temporary workers from the detailed occupation "assistants without further specification", which mostly appears in the industry group "Credit and insurance inter-mediation, land and housing, rentals". This industry group contains the subgroup "labor recruitment and provision of personnel" where temporary agencies are listed. Temporary work has increased a lot in Germany (Eichhorst and Tobsch, 2013).

large jumps associated with switches. However, the skill accumulation differentials are not large enough to drive a majority of earnings inequality. Part of this may be due to timing: For switches that occur after age 35, the skill accumulation differentials between occupation groups are not as big as they are at the beginning of careers. Nevertheless, the rise in the median and 85th percentile is large in Panels d and e in comparison to Panel c. In Appendix G.3, we show that this is due to the aging of the workforce with many more middle-aged workers at the median in 2010 compared to 1985. Demographic factors were therefore substantially responsible for the increase of lower half inequality. In contrast, since the 85th percentile was similarly raised as the median, upper half inequality did not increase much because of demographic changes or skill accumulation within occupations.

Adding the gains associated with occupation changes in Figure 9f raises all statistics; it does so disproportionately for the 85th percentile. This is not too surprising given the large coefficient estimates for switches into Mgr-Prof-Tech and Sales-Office occupations that we reported on in Section 4. Comparing the end points of our sample period, this scenario explains three quarters of the increase in the 85th percentile and the entire increase in the median; we are too optimistic about the evolution of the fifteenth percentile by 3 points. There are two things to note, however. First, the temporal pattern is very smooth and we do not track the intermittent evolution of any percentile very well. Second, there is actually a decline in the fifteenth percentile for the specification where we make unemployment or exiting the labor force a choice by filling such spells with the lowest adjacent wage (see Figure G.2 in the Appendix). This suggests that indeed careers at the lower end of the distribution became more fragmented and our main way of treating non-employment spells hides parts of this.

Comparing Figures 9f and 9b, we see that skill prices explain most of the remaining differences with the actual wage distribution. In particular, changing prices raise the 85th percentile as well as upper half inequality by an additional seven log points. As in the case of between occupation inequality, they thus have a strong impact. In the specification where unemployment is a choice, price changes hurt both the median and the 15th percentile, again highlighting that we overestimate the gains from switching at the lower end because occupation changes involving wage losses often go via an unemployment spell. Finally, adding the price changes allows us to track the temporal

evolution of all quantiles. Thus skill prices are not only aligned with employment across occupations, but they also align the temporal patterns of the wage distribution.

In sum, we show that initial occupational choices and demographic factors account for most of the increase in lower half inequality; alternative specifications suggests that more unstable employment biographies and adverse price developments have some role to play, too. This is consistent with the hypothesized effects in Dustmann et al. (2009), which is an important finding overall because it has previously been hard to rationalize polarizing demand for occupations together with wage inequality that increased across the board in most countries and time periods (Goos and Manning, 2007; Mishel et al., 2013; Green and Sand, 2015; Naticchioni et al., 2014). Occupational switches and changing skill prices have a particularly important role to play in the upper half of the wage distribution, driving almost all of the additional wedge that opened up between the 85th percentile and the median over the period 1985–2010.[42]

6 Discussion and Conclusion

This paper develops a model of occupation choice based on Roy (1951), which remains empirically tractable for many occupations and accommodates heterogeneous skill changes over the life cycle. We use this model to study how occupational employment growth relates to occupational wages and overall wage inequality. Our results indicate that skill-constant occupational wages *(skill prices)* evolved in a way that is consistent with occupational demand shifts. Skill selection of workers completely masked this relationship in raw occupational wages, where the development was unrelated to employment changes. We show that the systematic part of the skill price-employment growth nexus is due to what we term the *marginal selection effect*; net entry into an occupation multiplied with the skill differences between occupation entrants/leavers versus incumbents/stayers.

[42] The discussion in this section is robust to the more general acceleration/deceleration interpretation of skill price changes from Section 3.3. First, the full estimated model, which includes both skill accumulation and skill prices, is unaffected by this interpretation. Second, before the estimated prices are included, one would still like to add the average rates of price changes in the base period to the skill accumulation in order to obtain scenarios where "only" entry wages, initial occupations, or occupational switching changed. This is effectively what we do in Panels c–f of Figure 9.

The selection effect that we uncover is more subtle than the one considered in classic Roy models, where workers' skills across occupations are fixed over time. The classic effect accounts for less than forty percent of marginal selection in most occupations. The more important share is due to skill changes during employment stints in an occupation, i.e., the fact that incumbent/staying workers are positively selected, translating into longer tenure and gains from (specific) experience. These effects vary strongly across occupations, which is a reflection of the fact that occupational life-cycle wage profiles are very heterogeneous.

We further show that similar lines of reasoning carry over to wage inequality, where we establish a long-suspected connection to demand shifts and occupational employment changes that is meaningful also in quantitative terms. Worker (self-)selection leads to substantially lower wage inequality between occupations than would be observed if workers in the 1980s were given the skill prices of later decades while holding their occupational choices fixed. Selection thus makes it appear that occupational changes were not that important. Using our model to understand the trends in overall wage inequality, we instead find that differentially evolving skill prices and heterogeneous skill changes across occupations are the most important drivers of upper-half inequality. Initial occupation choice and population aging—which induces higher wages at the median of the wage distribution due to a larger fraction of seasoned workers—are the main factors driving lower-half inequality.

Our explanation is consistent with other accounts of rising wage inequality in Germany. One of the most prominent is based on de-unionization and a decentralization of the wage bargaining process (Dustmann et al., 2009, 2014). These phenomena have the strongest impact in the manufacturing sector, that is, the industry sector that is most important for the declining Prod-Op-Crafts occupations. We deem it plausible that demand shifts are a deeper cause for this, as unions and works councils understand their deteriorating bargaining position due to the threats of substitution by machines or foreign workers.[43] Our findings are also consistent with other work showing that German firms tend to upgrade labor through investment in skills (Battisti et al., 2017; Dauth et al., 2017).[44] These responses may reflect the institutional environment,

[43] Baumgarten and Lehwald (2019) provide evidence for the threat of import competition.

[44] We find few switches of occupations to be systematically associated with large losses, even if we fill intermittent spells of non-employment.

which results in relatively cooperative labor relations in Germany. For example, unions and works councils are represented on boards of large companies and thereby involved in managerial decisions.

The approach we develop in this paper differences out the unobserved skills in workers' chosen occupations. This helps solve the econometric selection problem without recurring to parametric assumptions on unobservables. It does, however, come at the cost of not identifying the full population distribution of skills. In the counterfactual analyses in this paper, we therefore condition on observed occupation choices. Other papers, by contrast, assume a static full distribution of skills (e.g., Gabaix and Landier, 2008; Hsieh et al., forthcoming) to study the effects of important changes in the U.S. economy on the allocation of talent and earnings. One promising avenue for further research is to combine these two approaches, and to obtain micro-identified levels and changes of skills across occupations. With efforts underway to link direct survey measures of skills to administrative records, the data requirements will be met in the near future. Our framework will provide a good starting point to model entire careers. The result would certainly promise to answer key economic questions and allow making predictions about future developments such as the further impact of big data and artificial intelligence.

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