Task Prices, Sector Growth, and Skill Selection: Evidence from a New Estimation Method

Michael J. Böhm, Hans-Martin von Gaudecker, and Felix Schran *

First draft: January 2017
Current draft: March 2018

Abstract

An intimate connection between routine-biased technological change and wage inequality has been discussed for a long time, yet it has proven difficult to find clear evidence for it. We add to this literature by developing an empirical model of sectoral choice to estimate changing task prices and skill accumulation across multiple sectors. Applying our method to Germany, we find that the prices for work in high-earning and low-earning occupations strongly increased compared to middle-earning occupations. Correlated task price and employment growth indicate that demand shocks are the main driver of occupational changes. This relationship is masked in observed wages by deteriorating skill selection of rising occupations. In particular, we show that low skills of net entrants to growing occupations can account for the majority of this effect. Both task prices and the induced changes in skills across occupations have had a substantial impact on surging wage inequality.

Keywords: Multisector Roy Model; Task prices; Skill Selection; Wage Inequality; German Administrative Panel Data
JEL codes: J23, J24, J31

---

* Böhm: University of Bonn and IZA, mboehm1@uni-bonn.de. Gaudecker: University of Bonn and IZA, hmgaudecker@uni-bonn.de. Schran: University of Bonn, felixschran@uni-bonn.de. We would like to thank Matias Cortes, Christian Dustmann, David Green, Thomas Lemieux, Uta Schönberg and Shintaro Yamaguchi as well as seminar and conference participants at U-Alberta, U-Bonn, U-British Columbia, UCL, U-Kiel, ESPE 2016, ZEW Mannheim, U-Michigan, SOLE 2017, and the Canadian Labour Economics Forum 2017 for very valuable comments. Böhm gratefully acknowledges support from a Research Fellowship of the German Science Foundation (BO 4765/1-2).

1 Introduction

Industrialized countries' employment and wage structures have shifted drastically over the last decades, with traditional manufacturing-type employment declining and wages becoming much more unequal (e.g. Acemoglu and Autor, 2011). Many explanations for these changes have been brought forward; among the most prominent ones are automation technology, international trade, and skill supply (Autor et al., 2003, 2013; Bowlus and Robinson, 2012).

But often the empirical evidence is seemingly inconsistent with even either shifts in the supply or the demand for skills taking place. For example, recent research has documented increasing labor productivity yet at the same time a shrinking workforce in the manufacturing sector (Young, 2014), or growing employment in high- and low-earning occupations with rising and falling average wages in these occupations, respectively (e.g. Dustmann et al., 2009; Naticchioni et al., 2014; Green and Sand, 2015). While several authors have noted that these findings may be due to confounding changes in skill composition (e.g. Firpo et al., 2013; Gottschalk et al., 2015; Böhm, 2017; Cortes, 2016; Cavaglia and Etheridge, 2017), it has remained empirically difficult to convincingly account for such selection effects.

In this paper, we propose a new method for estimating task prices, that is, selection-corrected wage rates, across multiple sectors in order to solve this problem. Our method is related to the sufficient statistics approach (see, e.g., Chetty, 2009, for an overview) in the sense that we find an approximation to an explicit economic model of sectoral choice, which can be estimated using standard linear panel data techniques. Our approach thus combines some of the advantages of structural methods with those of linear panel data estimators. We use the Roy model to link workers' wage growth to their endogenous sector choices, flexibly modeling sector-specific skill accumulation over the life-cycle. The linearity of the approximated wage equation facilitates estimation in large-scale datasets and with many sectors.

We apply the estimation method to high-quality administrative records from Germany during 1985–2010. We find that task prices, employment changes, and skill selection interact in systematic and important ways. First, task prices in high-earning managerial, professional, and technical and in sales and office professions as well as low-earning services and care professions have grown compared to middle-earning production, operator, and crafts professions.[1] Since employment in the Mgr-Prof-Tech, Sales-Office, and Srvc-Care professions has also grown and Prod-Op-Crafts professions are relatively intensive in routine manual tasks, this is consistent with routine-biased technical change or related forces impacting the German wage structure. We also estimate that skill accumulation is concave over the life-cycle and initially much steeper in Mgr-Prof-Tech and Sales-Office than in Prod-Op-Crafts and Srvc-Care professions.

More generally, we uncover a significant positive correlation between task prices and employment growth across the 120 detailed occupations underlying the broad professions, which indicates that shocks to demand rather than supply are the main drivers of changes in occupational outcomes over time. However, the positive relationship is offset by strongly deteriorating skill selection in rising occupations. This selection effect makes employment growth uncorrelated with changes in average wages across detailed occupations, which explains why linking sectoral employment to observed wage changes often leads to inconclusive results.[2] It also attenuates wage growth in the rising Mgr-Prof-Tech and Sales-Office professions, and it even overturns the effect of the rising task prices for the low-earning Srvc-Care profession.

We use additional evidence to corroborate and analyze the strong negative selection effect in rising occupations. We document that average wages of entrants as well as leavers in every occupation are substantially lower than of incumbents or stayers. In fact, the more an occupation grows, the lower its entrants relative wages Together with the high rate of net entry into (exit from) the growing (shrinking) occupations, these differences by themselves can account for the majority of selection effects

[1]We term broad occupation groups based on measured job task content that encompass managerial, professional, and technical (high-earning; 'Mgr-Prof-Tech'); sales and office (high-earning in Germany; 'Sales-Office'); production, operator, and crafts (middle-earning, 'Prod-Op-Crafts'); and elementary services and care (low-earning, 'Srvc-Care') as our four 'professions'.

[2]For example, Goos and Manning (2007) and Green and Sand (2015) find that in the U.K. and Canada, similar to this paper, average wages in growing high-skill occupations increased but they fell in growing low-skill occupations compared to shrinking middle-skill occupations. Mishel et al. (2013, p5) conclude from their analysis that there is "little or no connection between decadal changes in occupational employment shares and occupational wage growth" in the U.S..

implied in the estimation. Therefore, the prediction from the Roy model that marginal workers are less skilled than inframarginal workers, if the correlation between skills across sectors is less than perfect (McLaughlin and Bils, 2001; Young, 2014), is borne out in the data.

An important reason why the "marginal selection effect" is so strong, and the correlation between skills may be imperfect, is that incumbent workers accumulate substantial amounts of skills during their time in the sector before a marginal worker enters. This underscores the considerable attention that we pay to modeling workers' skill accumulation in our estimation. In particular, we document a set of stylized facts about workers' differential wage growth accross professions, switching behavior and associated wage changes that a realistic skill accumulation function needs to allow for. The resulting conceptual and empirical focus on changes in skills over time is a key distinction of our approach to existing estimations based on cross-sectional data or fixed effects. We also show to what extent the marginal selection effect and its skill accumulation part can be apportioned to new entrants into the labor market, profession switchers, and entrants from unemployment or out of the labor force.

Finally, we quantify the role of task prices and skill accumulation in the changing German wage structure. We find that our model accounts for at least half of the increase in inequality over a cohort's life-cycle and more than two thirds of the rise in cross-sectional inequality during the sample period. Task prices and skill accumulation contribute to these effects to approximately the same extent.

One potential limitation of our estimation method, which it shares with other panel data approaches that flexibly account for workers' life-cycle wage growth, is that we need a base period (1975–1984 in our data) during which we assume *relative* task prices to be constant in order to separately identify the skill accumulation parameters from the changing task prices. However, we show that even in instances where this assumption is violated, our method still correctly identifies accelerations or decelerations of task price growth during 1985–2010 compared to the base period. In many applications this is what one would be interested in.

Another potential limitation, which is again shared with other panel data approaches, are unmodeled idiosyncratic wage changes (e.g. due to skill shocks), which may systematically covary with workers' switches of professions. This generates an endogeneity bias in the estimates. We show analytically that our control variables for skill accumulation, which are fully saturated in past and current job choices, and an alternative instrumental variable strategy, based only on past job choices, largely account for the endogeneity. In fact both provide a lower bound to the true relative changes in task prices. If anything, the strong effects that we estimate are then less extreme than their true values.

We report extensive Monte Carlo simulations generating data as similar as possible to the actual dataset and showing that our method identifies the correct task prices under a rich model of skill accumulation, and that it provides tight lower bounds when idiosyncratic skill shocks are included.[3] The approximation we make for the wage gains when workers switch sectors does not bias the estimates. We also conduct a battery of robustness checks for our empirical results. These include, among others, checks on the plausibility of the identification assumptions as well as varying the period length, different age (sub-)groups, a women sample, alternative base periods, adding workers who are unemployed or out of the labor force in the estimation, and variations on the skill accumulation function.

Our study is most closely related to the literature which estimates task prices and skill selection in the presence of secular or cyclical changes. In particular, recent papers on long-run trends in the occupation (via routine-biased technical change 'RBTC') and industry (via structural transformation) structure have employed a set of approaches to estimate task prices or skill selection in cross-sectional data. This includes weighting on observables (Firpo et al., 2013), sorting of talent (Böhm, 2017), bounding (Gottschalk et al., 2015), and instrumental variables (Young, 2014). Other studies have used worker fixed effects (plus standard experience controls) in the context of RBTC (Cortes, 2016; Cavaglia and Etheridge, 2017) and when examining skill selection into industries over the business cycle (e.g. McLaughlin and Bils, 2001).

Compared to these approaches we propose a new method to estimate changes in task prices (and thereby selection effects) in panel data, which accounts for time-

[3] In contrast, an alternative approach based on fixed effects, which is comparably easy to implement to our method, has difficulty identifying the correct task prices under a realistic model of skill accumulation and it effectively breaks down with idiosyncratic skill shocks.

invariant worker differences as well as rich skill accumulation over the career.[4] The method is based on an explicit economic model of workers' sector choices and wage growth, does not rely on distributional assumptions, applicable for many sectors, easy to implement, and transparent in which empirical moments it uses for identification. We find polarizing task prices (consistent with e.g. Cortes, 2016; Böhm, 2017; Cavaglia and Etheridge, 2017) and deteriorating relative skills in the growing sectors (as in McLaughlin and Bils, 2001; Young, 2014). But we also show how task prices, employment changes, and skill selection are systematically related in general and we provide independent evidence to corroborate and analyze the strong negative selection effect for rising occupations. Much of this rests on workers' sector-specific skill accumulation, which makes up more than half of the selection effect in any given cross-section. Our estimation method explicitly accounts for this and therefore we are able to explain the often seemingly contradicting trends in occupational employment and wages.

The next section provides stylized empirical facts about changes in sectoral employment and average wages as well as the importance of skill changes for individual career dynamics. Section 3 presents the model and derives our new method for estimating task prices in panel data. Section 4 reports the empirical results and Section 5 analyses the negative skill selection effect on growing sectors. Counterfactual analyses using our estimates are conducted in Section 6 and the last section concludes.

2 Stylized Facts

2.1 Data

We use the Sample of Integrated Labor Market Biographies (SIAB) provided by the IAB institute at the German Federal Employment Agency for the empirical analysis. 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

[4] Yamaguchi in two recent studies has explicitly modeled skill accumulation in panel data employing distributional assumptions (Yamaguchi, 2012) and correlated random effects (Yamaguchi, 2016), respectively. Such more "structural" approaches, which also include the classic cross-sectional estimation by Heckman and Sedlacek (1985), critically rely on these assumptions and they become computationally very demanding for more than a couple of sectors (Heckman et al., 1998).

covered by social security, marginal part-time employment, benefit receipts, officially registered as job-seeking or participating in programs of active labor market policies. The SIAB excludes the self-employed, civil servants and individuals performing military service. Most notably, it contains an individual's full employment history, the occupation, industry, wage, and important socio-demographics such as age, gender, and level of education. The data is exact to the day as employers need to notify the employment agency if the employment relationship changes.

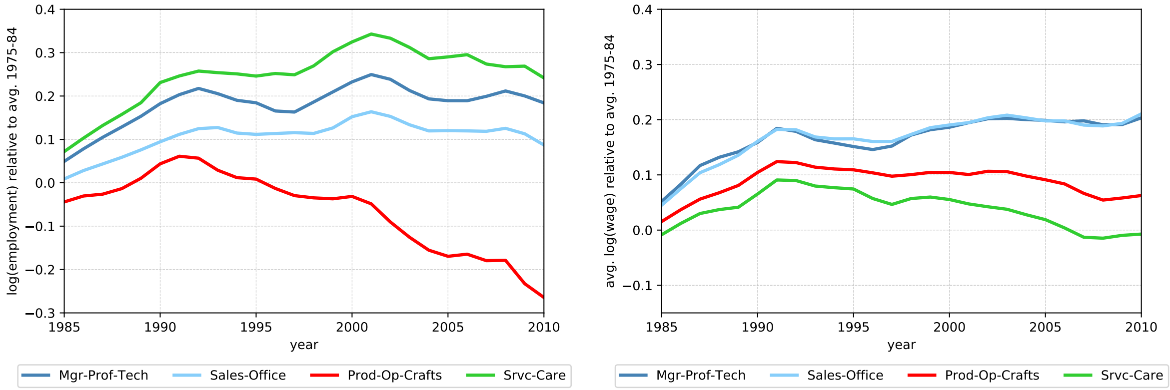
We restrict the main sample to full-time 25 to 54 year old German men working in former West-Germany. We transform the SIAB's spell structure into a yearly panel and extrapolate daily wages to obtain equivalent wages per year. To the greatest extent, we prepare the data, including the wage variable, as in Dustmann et al. (2009) and Card et al. (2013). A detailed description of the dataset construction is in appendix A.

We use detailed occupations as well as more aggregated occupation groups, which we term 'professions'. There are 120 different three-digit occupations consistently classified during 1975–2010 in the SIAB. We conduct all the analyses using these detailed occupations. However, in order to ease interpretation, we also follow Acemoglu and Autor (2011) and others to group the 120 occupations into broader professions based on their task content. These professions comprise managers, professionals, and technicians (Mgr-Prof-Tech; relatively intensive in *analytical* tasks); sales and office workers (Sales-Office; *interactive*); production, operators and craftsmen (Prod-Op-Crafts; *routine manual*); and services and care workers (Srvc-Care; *non-routine manual*). The task contents are summarized in Table A2. In robustness checks we additionally do the analyses for the ten sub-professions in these four aggregates.

One fact to note about the professions in Germany compared to other countries is that Sales-Office is quite high-earning. Figure A18 shows that its average wages 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 task prices for this profession below. The profession also scores high on non-routine interactive task content. Using survey data, Cavaglia and Etheridge (2017) document substantially higher average wages for sales and office occupations in Germany than in the U.K..

Figure 1: Professions' Wage and Employment Trends

(a) Employment (b) Wages



Source: SIAB data, own calculations. The left panel shows the log of employed persons within the four respective professions over time minus its average between the years 1975 and 1984. The right panel plots mean wages within those four professions over time minus the average across years between 1975 and 1984.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

2.2 Wages and Employment across Sectors

In this section, we present the major trends in employment across professions and wage inequality in Germany. We also provide initial evidence that selection effects may play an important role in determining average wages of growing versus declining occupations.

Panel (a) of Figure 1 shows that Germany has experienced a strong polarization of its employment structure over the last decades, in line with other major economies (e.g. Goos and Manning, 2007; Acemoglu and Autor, 2011). In particular, the employment share in Prod-Op-Crafts professions declined by more than 20 percent from a baseline share of more than 60 percent; employment in all other professions increased. These trends are termed 'job' or 'employment polarization', because Prod-Op-Crafts tend to be located in the middle of the occupational wage distribution. Figure A18 in the Appendix shows some additional background statistics.

The polarization of the employment structure – at least after the mid-1990s – coincided with a dramatic widening of the wage structure. Previous work has shown that overall wage inequality in Germany strongly increased after 1991 (e.g., Dustmann et al., 2009; Card et al., 2013, see Figure A18(e) for a verification in our sample). Panel (b) of Figure 1 shows that relative wages in high-earning Mgr-Prof-Tech and Sales-

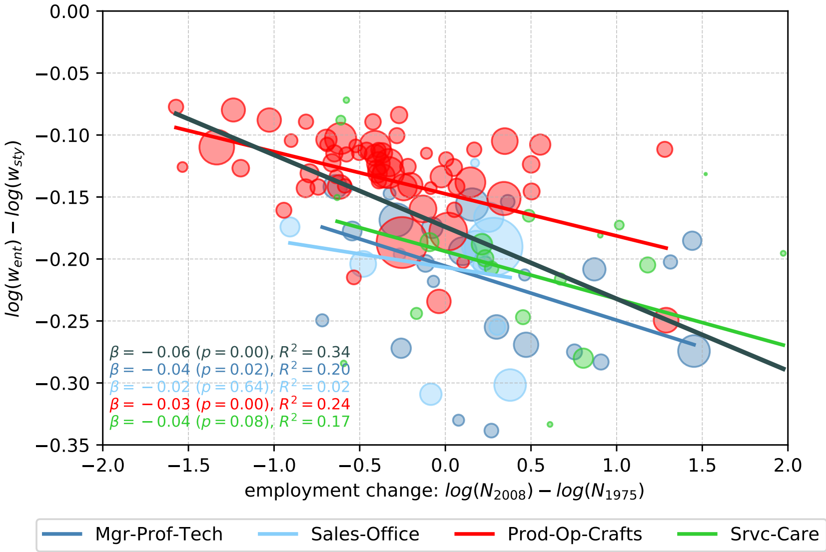
Office increased and they strongly fell in the low-earning Srvc-Care, with the shrinking and middle-earning Prod-Op-Crafts profession located in between.

While striking, these facts about the overall wage distribution and especially about average occupational wages are not easily reconciled with the trends in the employment structure. In particular, the most prominent explanation for the polarizing employment structure in developed economies is based on the replacement of routine work with automation technology (e.g. Autor et al., 2003; Acemoglu and Autor, 2011). Such a negative (relative) demand shock should indeed lead to the declining share of employment in routine-intensive professions (i.e. Prod-Op-Crafts) and to a rising share of employment in non-routine analytical (Mgr-Prof-Tech) and interactive (Sales-Office) as well as non-routine manual (Srvc-Care) professions, which we see in Figure 1(a).

But this should at the same time lead to wage gains in these growing professions, which certainly does not emerge as a clear pattern in Figure 1(b); for example, wages in Srvc-Care are falling even more than in Prod-Op-Crafts professions. Other potential demand shocks, for example based on trade and offshoring (e.g. Blinder and Krueger, 2013), should lead to the same predictions. A supply shock would lead to the inverse trends with rising wages in Prod-Op-Crafts compared to *all* other professions. Comparable and, at first glance, similarly surprising evidence exists for the United States (Mishel et al., 2013; Böhm, 2017), United Kingdom (Goos and Manning, 2007), Canada (Green and Sand, 2015), and a set of European countries (Naticchioni et al., 2014). In the literature about structural transformation, which studies employment and output trends across industry sectors, a related fact exists whereby sectors with rising employment shares experienced declining labor productivity (e.g. Young, 2014).

One potential explanation for these facts, which is still consistent with a relative demand shock driving both employment and wages, is based on selection effects. In particular, growing sectors on balance draw in additional workers whereas contracting sectors churn them out. If such marginal workers are less skilled in the respective profession than the incumbents or staying workers, this could lead to strong composition effects acting on average sectoral wages. In fact, in our data, workers who stay in their profession command substantially higher wages than either entrants or leavers.

Figure 2: Wages of entrants minus wages of stayers



Source: SIAB data, own calculations. One bubble in the graphs represents one of the 120 occupations in the SIAB data. The size of one bubble is proportional to the number of workers within one occupation. The vertical position was computed by subtracting the average log wage of occupational stayers from the average wage of entrants. Time trends in wages were taken out by means of a regression on a set of year dummies. The horizontal position was calculated by subtracting log employment in 1975 from log employment in 2010. The regression line in dark gray was fitted weighting each occupation by its size. The colored lines were fitted within the respective four professions. P-values are in parentheses.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Figure 2 depicts this for entrants and the detailed occupations. First, the negative positions of the bubbles show that entrants in *all* of the 120 occupations earn substantially less than incumbents. In our model below we interpret this as lower skills of entrants. Table A4 in the Appendix breaks this down further for entrants and leavers. Another finding in Figure 2 is that the wage (skill) differences between entrants and incumbents are larger the more an occupation grows over time. The pooled as well as the profession-specific regression lines are highly significantly negative in the graph. Importantly, this finding holds up when controlling for a large set of observables, see Figure A10 in the Appendix. This should reflect the fact that the skill pool that they can draw from narrows for strongly growing occupations, and it reinforces the potential negative selection effects induced by occupational growth.

Overall, Figure 2 shows that rising sectors tend to feature more lower-than-average-skilled entrants and fewer lower-than-average-skilled leavers than declining sectors. This suggests that substantial composition effects may develop which are *due to* sectors changing size and which may explain the trends in average sectoral wages. The remainder of our paper pursues this selection idea, proposing a panel data model to estimate changing task prices per unit of fixed labor which are cleaned of selection effects and thus reflect fundamental demand and supply for the respective professions and occupations.

2.3 Life-Cycle Dynamics

In this section, we document important empirical regularities about workers' careers that our panel data model for estimating task prices needs to capture. In particular, we show that there are systematically varying career paths with respect to workers' observed characteristics and prior professional choices, but also idiosyncratic differences between workers who are observably the same up until a given point in time.

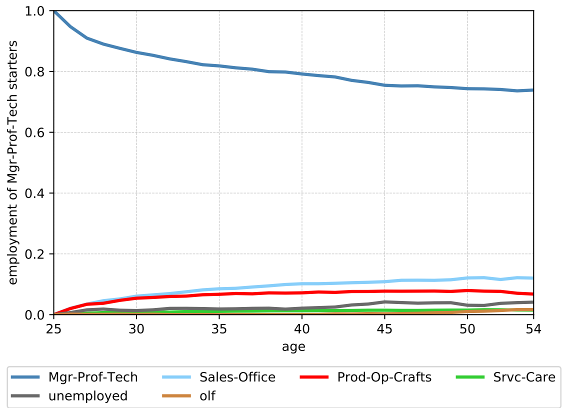
First, consider the systematic differences captured by observable characteristics. In Figure 3 we graph the employment shares and average sectoral wages of workers born in 1955–1965 by the sector in which they started their careers. These workers differ systematically in the sense that the starting profession is very predictive of later professions in life, especially for starters in Mgr-Prof-Tech occupations (Panel a).

The differences are potentially even stronger in terms of wages. Focusing on the black lines in the respective panels, average initial wages differ not only by about 30 log points between starters in Mgr-Prof-Tech and Srvc-Care professions, with Sales-Office and Prod-Op-Crafts professions in between, but also in terms of life-cycle profiles, whereby wage growth of Mgr-Prof-Tech starters is much higher (60 log points gain between age 25 and 50) and of Prod-Op-Crafts starters (20 log points gain) much lower than the other professions. These profiles suggest that workers accumulate skills over their careers and that this accumulation differs strongly by which occupations they work in.

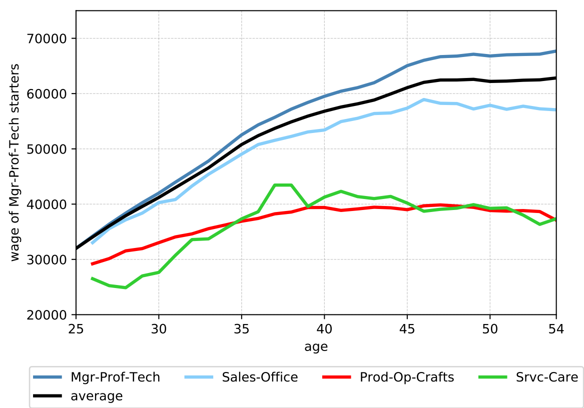
In fact, the history of professional choice seems to matter systematically even conditional on current professional choice, since, for example, within-career Sales-Office wages (light blue series) are much higher for starters in Mgr-Prof-Tech professions (Panel b) than for starters in Prod-Op-Crafts or Srvc-Care professions (Panels f and h). It is true that some of these differences reflect differences in occupation composition within the four broad professions, but they qualitatively remain when we do the same analysis for the 120 detailed occupations.

Figure 3: Employment and Wage Dynamics for Starters in the four Professions

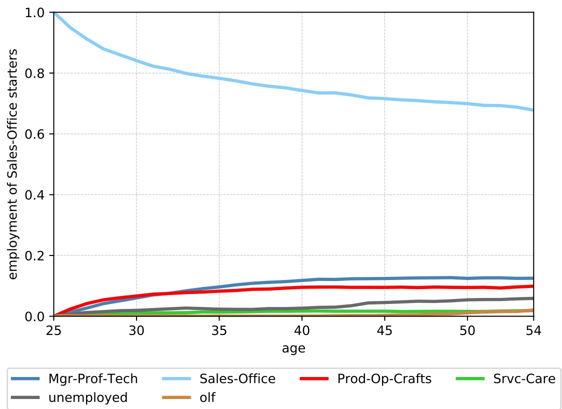
(a) Employment (Mgr-Prof-Tech)



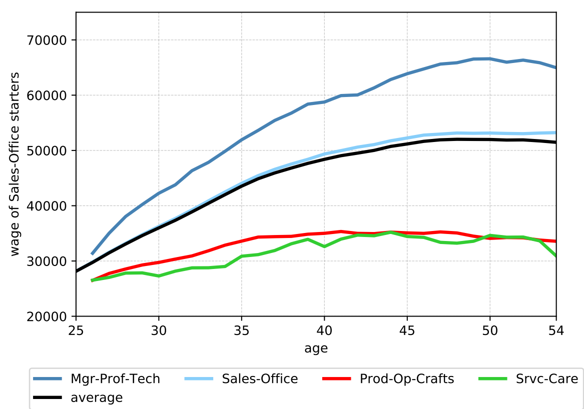
(b) Wages (Mgr-Prof-Tech)



(c) Employment (Sales-Office)

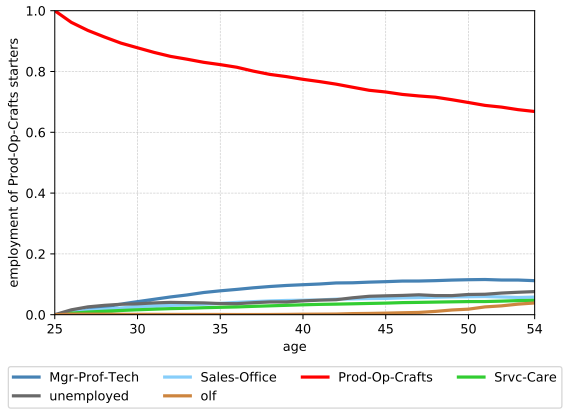


(d) Wages (Sales-Office)

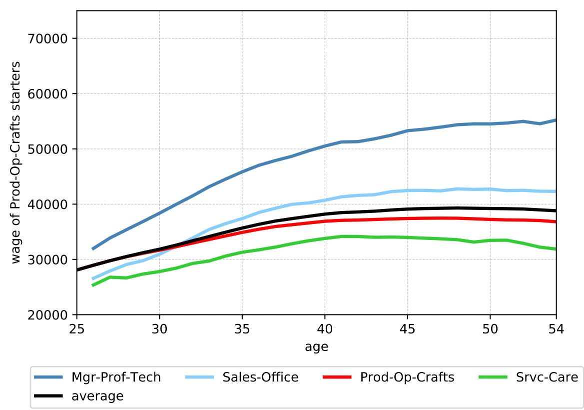


Our estimation model in Section 3 will capture the different systematic dynamics in workers' career profiles by profession or occupation, respectively. But it will also address important idiosyncratic differences across individual workers within these observable groups. In particular, the left panels of Figure 3 show that, despite the persistence of initial conditions, substantial heterogeneity in term of professional choices develops over the life-cycle. This is particularly strong for starters in Srvc-Care professions, less than half of whom work in their initial profession at age 50 (Panel g). This suggests that even within the same gender, age, and history of profession choice, substantial heterogeneity in career paths exists that cannot be modeled by observable

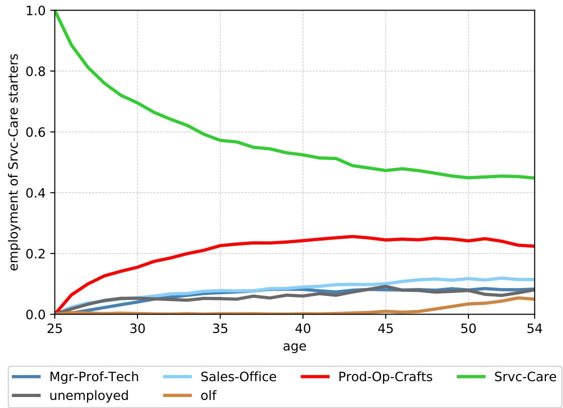
(e) Employment (Prod-Op-Crafts)



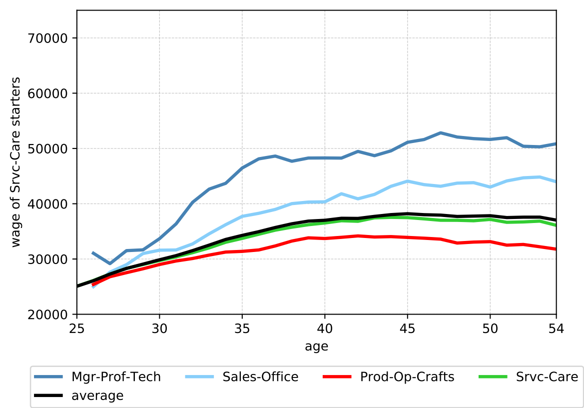
(f) Wages (Prod-Op-Crafts)



(g) Employment (Srvc-Care)



(h) Wages (Srvc-Care)



Source: SIAB data, own calculations. The left panels show employment probabilities of workers who started in a certain profession at age 25 indicated by the caption and following those workers over their life cycle from age 26 to 54. The right panels plot the average wages of these workers.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care; olf: out of labor force.

variables alone.[5]

In addition, there exists substantial heterogeneity in wages, which, critically, is systematically related to the heterogeneity in choices. In particular, starters in each of the three other respective professions have strikingly higher wages when they switch to a Mgr-Prof-Tech position (dark blue line) and strikingly lower wages when they switch to Prod-Op-Crafts or Srvc-Care roles (red and green lines) during their careers. This fact is underscored by Table A14, which shows that wages of workers who start out in a given profession at year $t-2$ strongly differ by the profession that they work in at year t. The inverse is also true, as Table A12 testifies by reporting the initial wa-

[5]We have also constructed the panels of Figure 3 conditioning on the same detailed occupation, level of education (e.g. apprenticeship), county of residence, and measured task intensities; and found qualitatively similar results.

ges of workers in a given profession at $t-2$ who ended up in different professions at t. Overall, this evidence suggests that different workers obtain for the econometrician unobservable positive and negative skill shocks during their careers, which make them change their occupations and at the same time impact their wages.[6]

Another fact which hints at such idiosyncratic skill shocks is the multi-directionality of workers' job switches. For example, in the left panels of Figure 3, there contemporaneously exist workers who switch from Prod-Op-Crafts to Mgr-Prof-Tech professions and workers who switch from Mgr-Prof-Tech to Prod-Op-Crafts professions, conditional on any set of observable variables.[7] In contrast, if workers' life-cycle dynamics were only driven by systematic skill accumulation or changing relative demand for professions (captured by the task prices in our model), we would expect them to conditionally move only in one direction (i.e. from Prod-Op-Crafts to Mgr-Prof-Tech). A realistic model of workers' career dynamics therefore needs to allow for idiosyncratic shocks as well as for the systematic skill accumulation discussed above.

Finally, note that there exists a difference, though modest, between average wages of starters in the respective profession (black line) and of stayers in that profession. This difference is also systematic in the sense that wages are higher for stayers than for all starters in Mgr-Prof-Tech jobs (Panel b), while they are lower for stayers than for all starters in Prod-Op-Crafts jobs (Panel f). An empirical strategy using only stayers would therefore not only select the sample on the outcome in terms of profession choices (i.e. left panels of Figure 3), but also in terms of wages (right panels), both driven by idiosyncratic skill shocks. This leads to biased results, as we show in our evaluation below of an alternative estimation strategy based on worker-occupation fixed effects.

3 A Model for Estimating Task Prices and Skill Selection

In this section, we develop an estimation method for changes in task prices that can accommodate the stylized facts on profession switches and wage growth. Our method

[6]Alternatively, employers could learn about workers' true skills over time (e.g., as in Altonji and Pierret, 2001; Gibbons et al., 2005). Our model below allows for both of these interpretations.

[7]It is indeed well-known that gross flows are much larger than net occupational mobility. For example, Carrillo-Tudela et al. (2016) document that the latter is only 10-15% of the former in the U.K..

is based on an economic model of workers' optimal sector choices, which we solve to yield a linear wage equation in first differences. We discuss how to model both systematic and idiosyncratic skill changes of workers in this context. In an extensive set of Monte Carlo experiments, we evaluate the performance of our method using a wide range of parameter values.

There are $k = 1, \ldots, K$ distinct professions and at time t, a worker i is endowed with a vector of skills $S_{i,t} = \begin{pmatrix} S_{1,i,t} & S_{2,i,t} & \ldots & S_{K,i,t} \end{pmatrix}$. His potential wages obtain as the product these skills and of profession-specific task prices paid for one efficiency unit of skill, $\Pi_t = \begin{pmatrix} \Pi_{1,t} & \Pi_{2,t} & \ldots & \Pi_{K,t} \end{pmatrix}$. Letting lowercase characters denote the logarithm of a variable, the basic equation for log wages thus is:

$$w_{k,i,t} = \pi_{k,t} + s_{k,i,t} \,\forall\, k \in \{1, \ldots, K\}. \tag{1}$$

An important objective of this paper is to estimate the evolution of $\pi_{k,t}$ over a period of several decades. We assume that workers maximize their incomes by choosing the profession in which they earn the highest wage:

$$w_{i,t} = \max\{w_{1,i,t}, \ldots, w_{K,i,t}\} \tag{2}$$

In general, it is difficult—even with rich panel data—to recover changes in task prices from changes in observed wages. Arguably, the most important reasons for this difficulty are endogenous sector choices and simultaneous changes in workers' skills. We address these in turn.

3.1 A Tractable Model of Sector Choice

Since choices are the solution to an optimization problem, by the envelope theorem, a marginal change in the potential wage at time t is:

$$dw_{i,t} = \begin{cases} dw_{1,i,t} = d(\pi_{1,t} + s_{1,i,t}) & \text{if } I_{1,i,t} = 1 \\ \qquad\vdots & \\ dw_{k,i,t} = d(\pi_{K,t} + s_{K,i,t}) & \text{if } I_{K,i,t} = 1, \end{cases}$$

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 profession k. We can rewrite this as:

$$dw_{i,t} = I_{1,i,t}dw_{1,i,t} + \ldots + I_{K,i,t}dw_{K,i,t} = \sum_{k=1}^{K} I_{k,i,t}dw_{k,i,t}. \quad (3)$$

Equation (3) states that a worker's observed wage grows by the same amount as the potential wage in his chosen profession for marginal changes to potential wages. These could be due to changes in task prices or skills.

In order to arrive at an expression in discrete time, we still need to take the wage effect of an endogenous profession switch into account. To do so, we integrate over Equation (3) from $t-1$ to t. With a slight abuse of notation—made precise in the detailed derivation in Appendix B.1.1—we arrive at:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_{k,i,\tau}dw_{k,i,\tau}. \quad (4)$$

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 observed wage change is equal to the change in his potential wage in the chosen profession (i.e., $\Delta w_{i,t} = \Delta w_{k,i,t}$). If the worker switches from some other profession k' to k, ($I_{k',i,t-1} = 1$,$I_{k,i,t} = 1$), he obtains part of the origin profession's wage gain (or loss) as well as part of the destination profession's wage gain with the relative size of these parts determined by the point of indifference.

In empirical analyses, Equation (4) is directly observable for profession stayers. For switchers, we need to approximate it because we cannot observe their point of indifference. We choose to linearly interpolate the choice indicators for $\tau \in (t-1, t)$:

$$I_{k,i,\tau} \approx I_{k,i,t-1} + \frac{I_{k,i,t} - I_{k,i,t-1}}{w_{k,i,t} - w_{k,i,t-1}}(w_{k,i,\tau} - w_{k,i,t-1}). \quad (5)$$

Defining $\bar{I}_{k,i,t} \equiv \frac{1}{2}(I_{k,i,t} + I_{k,i,t-1})$ and combining Equations (4) and (5), we obtain:

$$\begin{aligned}\Delta w_{i,t} &= \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta w_{k,i,t} \\ &= \sum_{k=1}^{K} \bar{I}_{k,i,t} \left(\Delta \pi_{k,t} + \Delta s_{k,i,t}\right)\end{aligned} \tag{6}$$

A detailed derivation is in Appendix B.1.2. Provided that skill changes are controlled for in an adequate manner, the first term of (6) suggests that task prices can be recovered from a regression of first-differenced wages on "average" profession choices $\bar{I}$, which are easily constructed in panel data with occupational identifiers. The crucial question is, of course, whether the approximation (5) is a good one.

The first point to note is that (5) is not an approximation at all for workers who stay in their profession. This also holds true for workers who switch professions (say, from k' to k) and whose wages in $t-1$ and t are symmetric around their points of indifference. In particular, the following holds exactly for such workers:

$$\begin{aligned} w_{k',i,t-1} - w_{k,i,t-1} &= w_{k,i,t} - w_{k',i,t} \\ w_{k,i,t} - w_{k',i,t-1} &= w_{k',i,t} - w_{k,i,t-1} \\ &= \frac{1}{2}(\Delta w_{k',i,t} + \Delta w_{k,i,t}), \end{aligned}$$

The first line is the definition of equidistance, the second and third lines reformulate this. The third line is exactly the same as Equation (6) for such workers. Taking the expectation across all individuals preserves the relationship under the approximation. In particular, individual switchers may well have different gains from switching as long as $E\left[(w_{k,i,t} - w_{k',i,t-1}) - (w_{k',i,t} - w_{k,i,t}) \,\middle|\, I_{k',i,t-1} = 1, I_{k,i,t} = 1\right] = 0$. Finkelstein et al. (2015) make a related approximation in a completely different context; they nicely illustrate the argument in their Figure 1. Within our model, there is no reason to expect a skewed distribution. If there were fixed costs of switching sectors, however, the resulting inertia may well lead to symmetry not to hold if there are net flows from one sector to the other. In Section 3.3 below, we report on an extensive set of Monte Carlo experiments showing that this becomes a quantitatively meaningful problem only for rather extreme costs. First, however, we outline our framework for skill accumulation over the working life.

3.2 Modeling Skill Accumulation

We model skill acquisition as learning-by-doing on the job, i.e., a worker's skills s in profession k change depending on his profession choice k' in the previous period:

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

The vector $X_{i,t-1}$ contains a constant and observable variables controlling the speed of skill acquisition or depreciation via the vector $\Gamma_{k',k}$. The arguably most important examples available to us are age and education; in some specifications we also include direct measures of job-related tasks, similar in spirit to Gathmann and Schönberg (2010) or Yamaguchi (2012). Note that this formulation contains a full set of interactions of the accumulation coefficients $\Gamma_{k',k}$ with the covariates $X_{i,t-1}$. The summation term in (7) thus maps the previous profession choice k' interacted with $X_{i,t-1}$ into skills in the current profession k. The random component $u_{k,i,t}$ denotes idiosyncratic skill innovations; we assume that the stacked vector $U_{i,t}$ is independently and identically distributed over time and across individuals. Substituting (7) into workers' wage growth (6) yields our baseline estimation equation:

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

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, however, they are not separately identified from each other because of the constant term in $X_{i,t-1}$; the first row of $\sum_{k'=1}^{K} I_{k',i,t-1} \cdot X_{i,t-1}$ is 1 and hence perfectly collinear with changes in task prices. This is not surprising: In our model, it is immaterial for the individual decision of whether a higher wage in a sector stems from an increase in prices or an improvement in skills. Looked at from another angle, an aggregate increase of skill accumulation in a given profession is observationally equivalent to task price growth in this profession for all aspects of our data.

Table 1: Relative Wage Growth by Age over Time

	absolute		relative to 1976 - 1984			
	1976 - 1984		1985 - 1995		1996 - 2010	
	[26 - 34]	[35 - 44]	[26 - 34]	[35 - 44]	[26 - 34]	[35 - 44]
Mgr-Prof-Tech	0.035	0.014	0.000	-0.001	0.009	0.004
Sales-Office	0.028	0.010	0.009	0.002	0.004	0.003
Prod-Op-Crafts	0.017	0.010	0.003	-0.001	-0.001	-0.001
Srvc-Care	0.020	0.010	0.007	0.003	-0.002	-0.002

Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.
Source: SIAB data, own calculations. The columns marked as absolute show average individual wage growth between two consecutive years of 26 - 34 and 35 - 44 year old profession stayers relative to 45 - 54 year olds in each profession. The averages were computed by pooling the years 1976 - 1984. The remaining four columns show those averages for the intervals 1985-1995 and 1996 - 2010 relative to the values between 1976-1984.
The number of observations used to compute each cell is extremely high. For instance, there are roughly 330,000 (370,000) observations aged 26 - 34 (45 - 54) between the years 1996 - 2010 observed in the largest sector Prod-Op-Crafts. Therefore, the standard errors are tiny, which is why we omitted to show them. Figure A11 in the Appendix shows average wage growth by year and sector and includes confidence intervals. Except for a more cyclical behavior of wage growth in Mgr-Prof-Tech and Sales-Office, there seem to be no large up or downward trends.

In order to separate task prices from skill accumulation, our key assumption is that the skill accumulation coefficients are time-invariant. Table 1 provides some empirical support for this being a reasonable approximation. Say a set of dummies for different age groups were the only covariates in $X_{i,t-1}$. Using only profession stayers, we subtract one age group's wage growth from another and task prices drop out: $\Delta w_{a,k,t} - \Delta w_{a',k,t} = \gamma_{k,k,a} - \gamma_{k,k,a'}$. The first two columns of Table 1 show this for younger age groups relative to 45–54 olds during 1976-1984, which will be our base period. The third to sixth columns show changes relative to these values for the 1985-1995 and the 1996-2010 periods, respectively. The latter numbers are all small relative to the baseline values and there seems to be no systematic pattern to them, either.[8]

With the assumption of time-constant skills at hand, we can now identify changes in task prices relative to a base period, say from $t = 0$ to $t = T_{\text{base}}$. We run the regression (8), setting $\Delta\pi_{k,t} = 0$ for all k in $t = 1, \ldots T_{\text{base}}$, distinguishing between three cases.

1. The simplest interpretation obtains when task prices during the base period are constant (i.e., $\Delta\pi_{k,t} = 0$ for $t = 1, \ldots T_{\text{base}}$ holds). All $\Gamma_{k',k}$ will be identified from the base period. Changes in task prices are identified for all professions for $t >$

[8]Note that aggregate skill accumulation within professions can still vary over time across professions due to selection effects: One may expect that it slows down if more older workers are working in a profession or that it speeds up if more educated workers are attracted over time.

T_{base}.

2. If *relative* task prices are constant, we need to further normalize with respect to a reference profession. Our aim is to investigate the reasons for shifts across sectors; not economic growth per se. So this is not a limitation. With aggregate wage growth that is similar across sectors in the base period, we cannot identify whether this came from task prices or skill accumulation. Normalizing with respect to a reference profession k_{ref} allows us to identify all parameters of $\Gamma_{k',k}, k' \neq k_{\text{ref}}$ in relative terms from the base period. For example, the intercept $\gamma_{k,k',1}$ is just the wage growth of workers who work in k' during the previous period and in k during the current period minus the wage growth of workers who stay in k_{ref}. For $t > T_{\text{base}}$, task price changes relative to k_{ref} are identified via the acceleration of wage growth in k compared to the acceleration in k_{ref}. That is, $\Delta\pi_{k,t} - \Delta\pi_{k_{\text{ref}},t}$ given that we assumed $\Delta\pi_{k_{\text{ref}},t'} = \Delta\pi_{k,t'}, t' \in 1, \ldots, T_{\text{base}}$.

3. If there were differential trends in task prices between $t = 1$ and $t = T_{\text{base}}$, the interpretation changes relative to case 2.; the same coefficients are now interpretable as accelerations or decelerations of the previous trend. Say routine-biased technical change led to a relative decline of task prices for production workers already during the base period. If this was the reference profession, a positive task price for managerial professions would mean that this trend got stronger in later periods. This is still an important parameter for understanding the stylized facts presented in Section 2 because it summarizes how conditional wage growth of workers in different professions has accelerated or decelerated over time and thus affected choices, skill selection, and wages.

In our interpretations, we mainly stick to case 2., noting at various points the caveat that case 3. may be the more appropriate interpretation depending on the assumptions one is willing to make about relative task prices in the base period. We will also check robustness with respect to using different base periods.

We have not said anything about the shocks $u_{k,i,t}$ yet; their properties are of course crucial for the estimation and for the interpretation of the coefficients. We assume that

$u_{k,i,t}$ is an innovation with respect to the previous period in the sense that its expectation conditional on all predetermined variables is zero, i.e.,

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

Other than that we allow for any joint distribution function $F(u_{1,i,t}, ..., u_{K,i,t})$ of the unobservables so that, for example, idiosyncratic skill shocks can be correlated among similar professions in an unrestricted way. Bringing Equation (8) into the usual regression form by writing out the summations and considering only the observed sector choice trajectory from $t-1$ to t, the error term becomes $v_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t} u_{k,i,t}$. This structure of shocks of course introduces a correlation between the error and the regressors – a large innovation in a particular sector makes it more likely that choosing this sector happens to be optimal. We first show that a basic OLS regression of the model discussed so far is often robust to this effect; we then outline an instrumental variables strategy.

The regression (8) is a saturated skill model including all combinations of profession choices $I_{k',i,t-1}$ and $I_{k,i,t}$. In the base period, the regression becomes:

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

$$E\left[\sum_{k=1}^{K} \bar{I}_{k,i,t} \left(\sum_{k'=1}^{K} I_{k',i,t-1} \cdot X_{i,t-1} \cdot \Gamma_{k',k} + u_{k,i,t}\right) \middle| \left\{I_{k,i,t}\right\}_{k=1}^{K}, X_{i,t-1}\right] \quad t = 1, \ldots, T_{\text{base}}.$$

This identifies the conditional expectation function from the fully interacted base period regression. This also yields expected skill accumulation $E\left[\Delta s_{k,i,t} \middle| \left\{I_{k,i,t}\right\}_{k=1}^{K}, X_{i,t-1}\right]$. Defining $\nu_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t} \left[\Delta s_{k,i,t} - E\left[\Delta s_{k,i,t} \middle| \left\{I_{k,i,t}\right\}_{k=1}^{K}, X_{i,t-1}\right]\right]$, the regressions with observed wages as the dependent variable can be re-written as:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta\pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t} E\left[\Delta s_{k,i,t} \middle| \left\{I_{k,i,t}\right\}_{k=1}^{K}, X_{i,t-1}\right] + \nu_{i,t}, \tag{9}$$

Conditional on any combination of $I_{k',i,t-1}$ and $I_{k,i,t}$, the expectation of $E\left[\Delta s_{k,i,t} - E\left[\Delta s_{k,i,t} \middle| \left\{I_{k,i,t}\right\}_{k=1}^{K}, X_{i,t-1}\right]\right]$ is zero by construction. Therefore, if

$E\left[\Delta s_{k,i,t}\middle| \{I_{k,i,t}\}_{k=1}^{K}, X_{i,t-1}\right]$ is consistently estimated in the base period, the error term in regression (9) is uncorrelated with the regressors $\bar{I}_{k,i,t}, X_{i,t-1}$ and the correct changes in task prices are identified even under general idiosyncratic skill shocks.

An alternative approach to remove the bias in Equation (8) is by instrumenting the regressors $\left\{\bar{I}_{k,i,t}\right\}_{k=1}^{K}$ with their predetermined components $\{I_{k',i,t-1}\}_{k'=1}^{K}$, which are not a function of $u_{k,i,t}$. This leads to an estimation very similar to the dynamic panel data models pioneered by Arellano and Bond (1991), the only difference being the construction of regressors $\left\{\bar{I}_{k,i,t}\right\}_{k=1}^{K}$.

Finally, notice that in both approaches, the estimates $\Gamma_{k',k}$ do not correspond to the structural skill accumulation parameters in Equation (8). The reason in the IV is that if $\bar{I}_{k,i,t}$ are instrumented with lagged choices $I_{k',i,t-1}$, only one set of coefficients $\Gamma_{k'}$ for each past sector can be identified. In the case of an age dummy in $X_{i,t-1}$, this coefficient provides the average wage growth due to skill accumulation (including due to switching) for an individual working in profession k' in the previous period whose $X_{i,t-1}$-values are zero. In the OLS model, the $\Gamma_{k',k}$ are the averages of skill changes, whether systematic or idiosyncratic shocks, of $k' \neq k$ switchers or $k' = k$ stayers.

3.3 Monte Carlo Evidence and Model Extensions

Appendix C reports extensive Monte Carlo experiments to assess the validity of the new estimation method in data simulated to resemble the SIAB sample. As expected, the approximation (5) does not affect the correct estimation of task prices and skill accumulation, even when workers face substantial costs for switching sectors. Idiosyncratic skill shocks as in Equation (9) moderately downward-bias the estimated relative task prices – the estimates therefore provide a lower bound to the true changes in task prices – but even with arguably large variances of these shocks the bias is very limited.

Finally, the interpretation of the model in Sections 3.1–3.2 can be widened to include such extensions as learning about skills, switching costs, non-pecuniary benefits, and workers' forward-looking decision making. The learning result 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 of learning about an individual's skills over time. The other results are obtained from solving the generalized Roy model including additive-in-logs switching costs, non-pecuniary benefits, or continuation values. If these factors do not change systematically with the task prices over time, this results in a wage Equation (6) with simply an additional summand and it leads to generalized skill accumulation parameters. For a detailed discussion refer to Appendix B.2.

4 Estimation Results

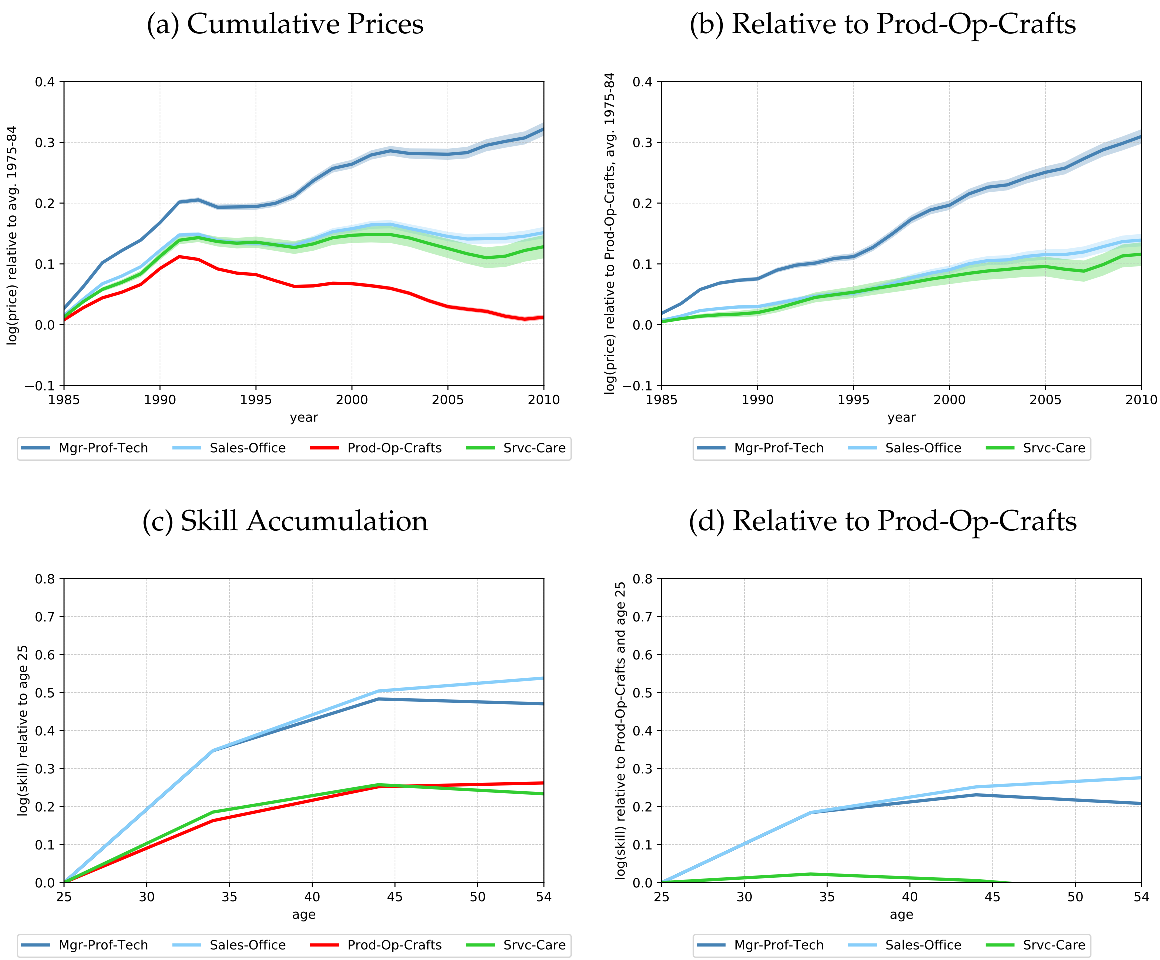
Figure 4a shows the cumulative task price changes (i.e. changes in selection-corrected wages) over time $\pi_{k,t} = \sum_{\tau=1985}^{t} \Delta\pi_{k,\tau}$, normalized to zero in 1984.[9] Task price grew strongly across the board in the second half of the 1980s until 1990 with an increase between 9 log points for Prod-Op-Crafts and 17 log points for Mgr-Prof-Tech. This is in line with almost equally fast real log wage growth during that period (Figure A18e). Upon reunification task price growth slowed down sharply and even decreased until about 1997, after which we observe a broad side-ward movement until the end of the sample period.

The focus of analysis in our paper are changes in the employment and wage structure. While level changes in task prices are informative for this, they may to a substantial extent reflect aggregate productivity growth or wage moderation after the reunification shock and the resulting surge in unemployment during the 1990s. Therefore, we focus in the following on *relative* task prices, in particular the comparison between the large but shrinking Prod-Op-Crafts profession and the other three professions.

We see that task prices already spread out during the 1980s, with the highest growth in the highest skilled Mgr-Prof-Tech profession and the lowest growth in the routine Prod-Op-Crafts profession. After reunification this spread briefly slows down but continues and after the mid-1990s it strongly accelerates. In 2010, at the end of the sample period, Mgr-Prof-Tech task prices have increased by 29 log points ($\approx$ 34%), Sales-Office by 15 log points (16%), and Srvc-Care by 12 log points (13%). Task prices

[9] Figure A12a presents the estimated incremental task price changes from period to period.

Figure 4: Estimated task prices and skill accumulation



Source: SIAB data, own calculations. The upper left panel show the estimated cumulated task price changes over time normalized to zero in 1984. The lines in the upper right panel were computed by subtracting the cumulated price changes of Prod-Op-Crafts from the other prices. Shaded areas represent the 95% confidence intervals computed by adding up the standard errors of price changes and their covariances. Standard errors are clustered at the individual level. The prices were estimated using the main sample of full-time male workers, aged 25 - 54, dropping permanent foreigners as well as spells from East Germany. The bottom left panel shows the estimated skill accumulation parameters $\hat{\gamma}_{k,k,a}$ for stayers, i.e. $k' = k$. Skills (in logs) are normalized to be zero at age 25. The results are presented in accumulated form $\sum_{\text{age}\in a} \hat{\gamma}_{k,k,a}$ over the ages in the life cycle. Again, the lines in the bottom right panel show the estimates relative to Prod-Op-Crafts.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

for Prod-Op-Crafts occupations have essentially stagnated and they actually declined by 8 log points after 1991.

Figure 4b graphs the relative task prices explicitly by subtracting the cumulative Prod-Op-Crafts series from the other three task price series at each point in time. Again we see the strong increase of relative Mgr-Prof-Tech task prices and the slower but equally secular increase in relative Sales-Office and Srvc-Care prices over the sample period. To put it in simple words, controlling for skill accumulation, workers' wage growth in high-earning Mgr-Prof-Tech and Sales-Office as well as low-earning Srvc-Care professions accelerated relative to middle-earning Prod-Op-Crafts ("polarized") during 1985–2010 compared to the base period of 1975–1984.

The results reported in Figure 4 are in notable contrast to the evolution of 'naive' average wages in professions depicted in Figure 1 above. Mgr-Prof-Tech but also Sales-Office task prices rise much stronger than their average wages compared to Prod-Op-Crafts. But most striking is the evolution of services professions, which even see their relative wage facts turned around. Whereas average wages drop compared to Prod-Op-Crafts, the services task prices actually rise significantly. This reversal implies that the broad trends in the employment and wage structure over the period 1985–2010 are in fact consistent with a rise in relative demand for high- and low-earning professions at the expense of the middle-earning Prod-Op-Crafts profession, despite the falling average wages in services. In particular, given the task content of these four broad occupation groups, the result is consistent with substantial impact of routine biased technical change on the German labor market but also with other hypotheses that would lead to a polarization in the demand for occupational skill content.[10]

The other main implication of Figure 4 is that it implies strong negative selection effects of skills into the rising professions. We conduct the detailed analysis of this in the next section, but we already discuss an important component of it here. Figure 4c

[10]This conforms with results in other studies estimating task prices either for the US (Cortes, 2016; Gottschalk et al., 2015; Böhm, 2017), the UK (Cavaglia and Etheridge, 2017) or Germany (Cavaglia and Etheridge, 2017). The finding is consistent with a substantial impact of routine-biased technical change, which proposes that the reduction in the price of computer capital led to a decrease in the relative demand for production tasks as those can be substituted most easily (Autor et al., 2003; Acemoglu and Autor, 2011). However, it is also consistent with increased competition facing Prod-Op-Crafts workers from abroad through intensified offshoring possibilities (Goos et al., 2014) or with spillovers from high-earners' consumption demand to low-earning services occupations (e.g., Mazzolari and Ragusa, 2013).

plots the estimated skill accumulation coefficients for stayers in the four professions. In particular, it shows the average skill accumulation by age of a (hypothetical) worker who was employed within one sector for all of his life by adding up the estimated $\gamma_{k,k,a}$ over the respective ages. First, we see that for all professions skills accumulate fast during the early years of the labor market career, slowing down during middle age, and then coming to a complete halt after the mid-40s. That is, skill accumulation is strongly concave over the life cycle, i.e. $\gamma_{k,k,a} > \gamma_{k,k,a'}$ for $a < a'$. This finding is consistent with a large literature on the concavity of wage profiles (e.g., Lagakos et al., 2018).

Table 2: Estimates for $\gamma_{k',k,a}$

k'	k	$[25, 35)$	$[35, 45)$	$[45, 55)$
Mgr-Prof-Tech	Mgr-Prof-Tech	0.039	0.014	-0.001
	Sales-Office	0.119	0.036	-0.004
	Prod-Op-Crafts	0.058	0.006	-0.025
	Srvc-Care	0.045	-0.006	-0.013
Sales-Office	Mgr-Prof-Tech	0.146	0.056	0.022
	Sales-Office	0.039	0.016	0.003
	Prod-Op-Crafts	0.092	0.035	0.002
	Srvc-Care	0.069	0.003	-0.009
Prod-Op-Crafts	Mgr-Prof-Tech	0.116	0.063	0.030
	Sales-Office	0.077	0.040	0.004
	Prod-Op-Crafts	0.018	0.009	0.001
	Srvc-Care	0.021	0.001	-0.009
Srvc-Care	Mgr-Prof-Tech	0.127	0.076	0.033
	Sales-Office	0.141	0.068	0.003
	Prod-Op-Crafts	0.129	0.076	0.028
	Srvc-Care	0.021	0.007	-0.002

Source: SIAB data, own calculations. The table shows the estimated $\hat{\gamma}_{k',k,a}$ for age groups a. k' is last period's profession. k is the current profession.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Second, skill accumulation, especially during young years, is considerably faster in high-skilled Mgr-Prof-Tech and Sales-Office professions than in middle- or low-skilled Prod-Op-Crafts and Srvc-Care professions. In particular, managers, professionals, and technicians as well as sales and office workers experience a skill increase of ca 50 log points between ages 25 and 54. The increase is only half for Prod-Op-Crafts and Srvc-Care workers (25 log points) with indication of skill depreciation after age 44 for services. Notice we are plotting here the wage growth of stayers from one period to the other in the different professions. This becomes especially noteworthy when skill shocks and endogenous switching of professions are important (see Section 3.2). However, it is clear from Figure 4c that skill accumulation, and thus baseline wage growth without any changes in task prices, differs substantially by profession and by age.

Table 2 reports all the $\hat{\gamma}_{k,k,a}$ skill accumulation parameter estimates, including those for switches. We see that staying in as well as switching to Mngr-Prof-Tech and Sales-Office professions is particularly profitable in terms of wage growth and especially so at a relatively young age. This is consistent with high skill accumulation in these professions and positive idiosyncratic skill shocks for those workers who make such switches. The table also shows that switching is often associated with positive wage growth, at least compared to staying in the respective profession. This is partly the case because in our main estimation we only include switches without intermittent unemployment, which are most likely voluntary. In robustness checks below we include intermittent unemployment in the estimation and the respective switching parameters to lower-earning professions (especially at older ages and in Srvc-Care) turn out accordingly lower (reassuringly without any substantive changes in the task price estimates).

The top row of Figure A15 depicts task prices if we ignore life cycle skill accumulation in the estimation. First, estimated prices increase much faster as they now erroneously include career wage growth. This would not be a problem for the *relative* prices if skill accumulation was the same for all professions. However, the data reject this hypothesis because life cycle wage growth is much stronger for high wage professions than for low and middle wage professions. Therefore, both absolute and relative price estimates of Mgr-Prof-Tech as well as Sales-Office grow much faster than in the estimates obtained by including skill accumulation controls.[11] The relative service pri-

[11]In the bottom row of Figure A15, applying one specification in Cortes (2016, p94, eq(8)), which allows for profession-specific experience profiles but not profession-specific experience, to our sample leads to almost identical results without any controls for skill accumulation. This suggests that this specification largely ignores these important aspects of skill accumulation as discussed in Appendix B.3.

ces, however, are similar to the ones including skill accumulation, which reflects the fact that the skill growth profiles of Prod-Op-Crafts and Srvc-Care professions are similar.[12]

We end this section by examining the relationship between employment growth and task prices versus average wages more generally. Panel (a) of Figure 5 depicts estimated changes in task prices for the detailed 120 occupations in our dataset together with their employment growth over 1984–2008.[13] We see that even for detailed occupations there is a clear positive relationship between task prices and employment growth, which notably was not used in the estimation. This is consistent with demand shocks for occupations driving both task price and employment changes across occupations. The dashed (sub-)regression lines corroborate this positive relationship *within* Mgr-Prof-Tech, Sales-Office, Prod-Op-Crafts, and Srvc-Care occupations although they are somewhat flatter, which might be due to a relatively larger influence of sampling variability that leads to attenuation bias.

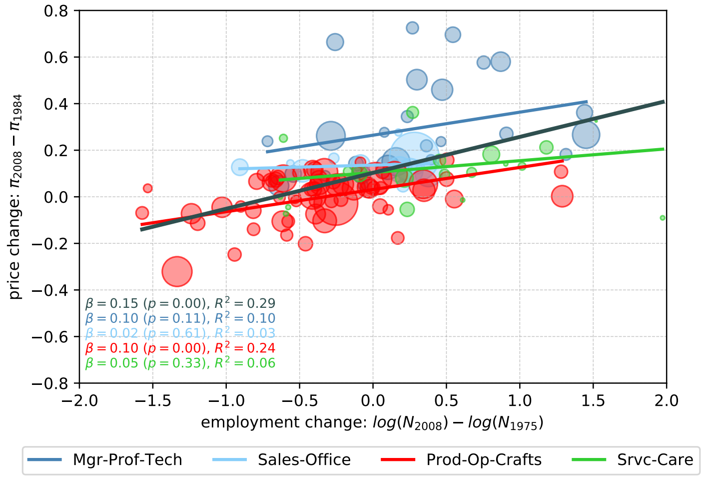
In stark contrast to Figure 5a, changes in average wages are not correlated with employment changes in Panel (b) of the Figure. This underscores the same finding for the four broad professions from above but now using 120 detailed occupations. It also implies that trends in average wages are not in general informative about demand changes across sectors and that we need to estimate the task prices for this. The flipside of this result is the strong decline of average skills in the growing occupations depicted in Panel (c) of Figure 5c. Again, this is not imposed in any way by our method, since employment changes are not used in the estimation. But it is consistent with the reasoning of the Roy model that marginal entrants into occupations may be less skilled than incumbents; and with the stylized empirical facts presented in Figure 2 above, whereby entrants into professions have lower average wages than stayers and

[12]Another problem that arises when ignoring skill accumulation are changes in the age distribution of employment. Imagine, for instance, that a lot of young workers enter the labor market within a certain year as was the case when the babyboomers entered the labor market between 1980 and 1990. If workers' life cycle accumulation of skill is concave, then the entry of a large, young cohort leads to an increase in average wage growth because of more overall skill accumulation. Thus, ignoring skill accumulation by age leads to an overestimation of task price changes. The reverse happens when young entering cohorts become smaller over time, as in recent years, making the work force age.

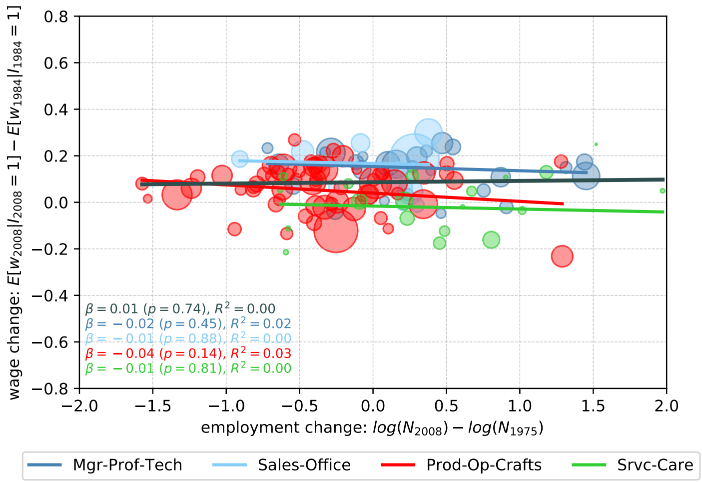
[13]We use four-year periods here as in Appendix D.1.2 to reduce the number of dummy variables in the estimation.

Figure 5: Relation of employment with task prices, and skill selection (120 occupations)

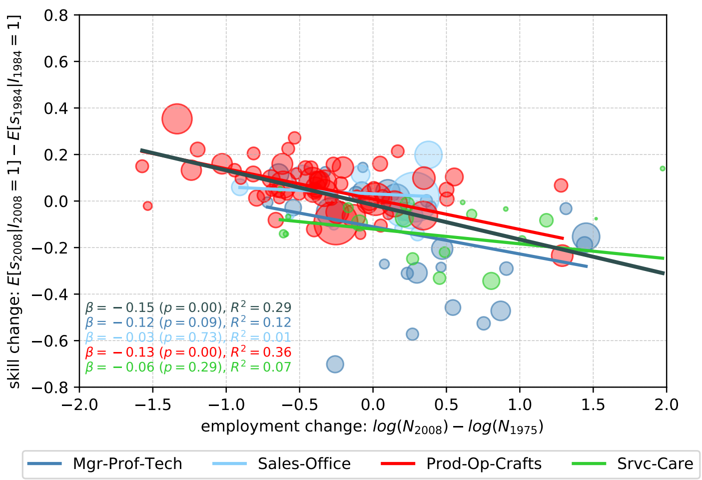
(a) Employment Changes and Task Prices



(b) Employment Changes and Observed Wages



(c) Employment Changes and Skill Changes



Source: SIAB data, own calculations. One bubble in the graphs represents one of the 120 occupations in the SIAB data. The size of one bubble is proportional to the number of workers within one occupation. The first panel shows the estimated change in the task price between 2008 and 1984 against the change in log employment. The middle panel shows the change in average wages. The bottom panel shows the implied change in skills. The regression line in dark gray was fitted weighting each occupation by its size. The colored lines were fitted within the respective four professions. P-values are in parentheses.

growing professions experience net entry. The next section will examine this effect in detail and show that it can also quantitatively match a large part of the implied decline of skills from the estimation method.

Finally, the deviations of the bubbles from the overall regression line in Figure 5a are potentially informative about elasticities of labor supply to different occupations. As employment grows, the bubbles for Mgr-Prof-Tech are mostly to the right of the graph. However, they are substantially above the regression line, which shows that wages grow relatively strongly compared to the growth in employment. This would be the case if labor supply to the Mgr-Prof-Tech professions is rather inelastic, that is, they require a high price change for a given employment change, which we think is plausible. More formally, the regression lines for Mgr-Prof-Tech but also Prod-Op-Crafts are steeper than for Sales-Office and Srvc-Care. This suggests that labor supply to the former is less elastic than to the latter.[14] Therefore, also in this respect, the estimates align well with an economic model of changes in demand for professions or occupations that drive employment, task prices, and skill selection; but at the same time the relative strengths of the changes in each profession or occupation are also a function of its labor supply.

Summary of Robustness Checks: We conduct a battery of robustness checks for the estimation results of this section. First, we validate the identification assumption that the skill accumulation function is time-invariant by examining wage growth within professions over time and estimating the task prices separately for different age groups. We then estimate the task prices in different samples, including foreigners and women, different base periods, longer period lengths, and workers who are unemployed or out of the labor force. We also run additional specifications where we extend the skill accumulation function by education level and actual task done in detailed occupation, split the four broad ones into ten sub-professions, instrument (endogenous) current with (exogenous) last period profession choices, and employ the

[14]The skill selection responses in Mgr-Prof-Tech and Prod-Op-Crafts are also stronger than in Sales-Office and Srvc-Care, which implies that there is a relatively high variability of skills in these professions and thus inelastic labor supply. But part of these differences in steepness may also reflect the aforementioned stronger influence of measurement due to sampling variability, since Sales-Office and Srvc-Care are much small professions and Prod-Op-Crafts is the largest and thus presumable "best-measured" profession in terms of employment changes.

alternative fixed effects estimation approach.

The empirical results in these different samples and specifications indicate that, among others, our results are largely robust to such considerations as workers' forward-looking behavior, alternative forces affecting women and minorities, choice of base period, switching costs, modeling of unemployment, occupation grouping, and some potential endogeneity concerns. Appendix D.1 discusses each robustness test in detail and reports the estimates.

Key assumptions or concerns that go beyond this wider interpretation are addressed using empirical robustness checks in Appendix D.1. This includes, among others, longer period lenghts, alternative age groups, more detailed professions, and different base periods as well as including workers who are unemployed or out of the labor force in the estimation.

5 Sector Growth and Skill Selection into Professions

This section analyses the selection of skills into professions implied by the task prices. We show that employment growth and rising task prices are associated with negative selection even within detailed occupations. We also use independent evidence from marginal entrants to qualitatively and quantitatively asses the potential impact of professions' employment growth on the decline in skills. Finally, we show that differences in profession-specific skill accumulation are an important part of the selection effect.

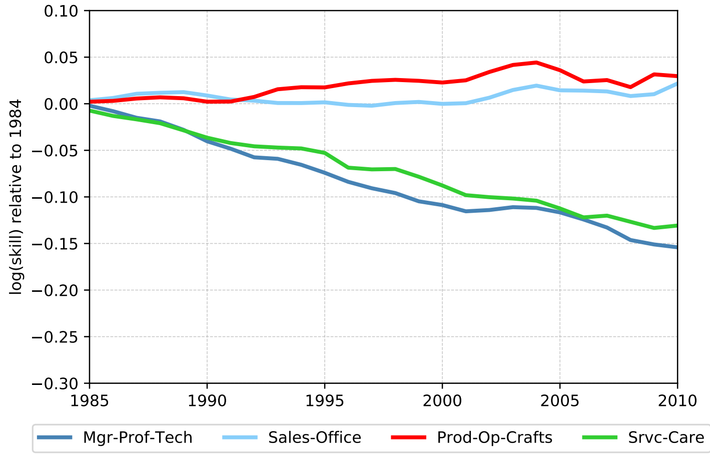
Figure 6 graphs the mean cumulative skill change for each profession over time[15]

$$\begin{aligned}\underbrace{\mathrm{E}[w_{i,t}|I_{k,i,t}=1]-\mathrm{E}[w_{i,t-1}|I_{k,i,t-1}=1]}_{\text{mean wage change}} = & \underbrace{\Delta\pi_{k,t}}_{\text{price change}} \\ & + \underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1]}_{\text{mean skill change}}\end{aligned} \tag{10}$$

This skill change is "implied by the estimation" because we calculate it as the difference between the observed change in the average wage (Figure 1b) and the estimated task prices (Figure 4a). The results show the flip-side of the discussion in the previ-

[15]Remember: $w_{i,t} = \pi_{k,t} + s_{k,i,t}$ if $I_{k,i,t} = 1$.

Figure 6: Implied skill selection



Source: SIAB data, own calculations. The lines show the estimated skills relative to the pre period for each profession. The estimates were received by subtracting the estimated prices changes from the mean wage differences between t and $t-1$ within the respective professions and accumulating those changes over time.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

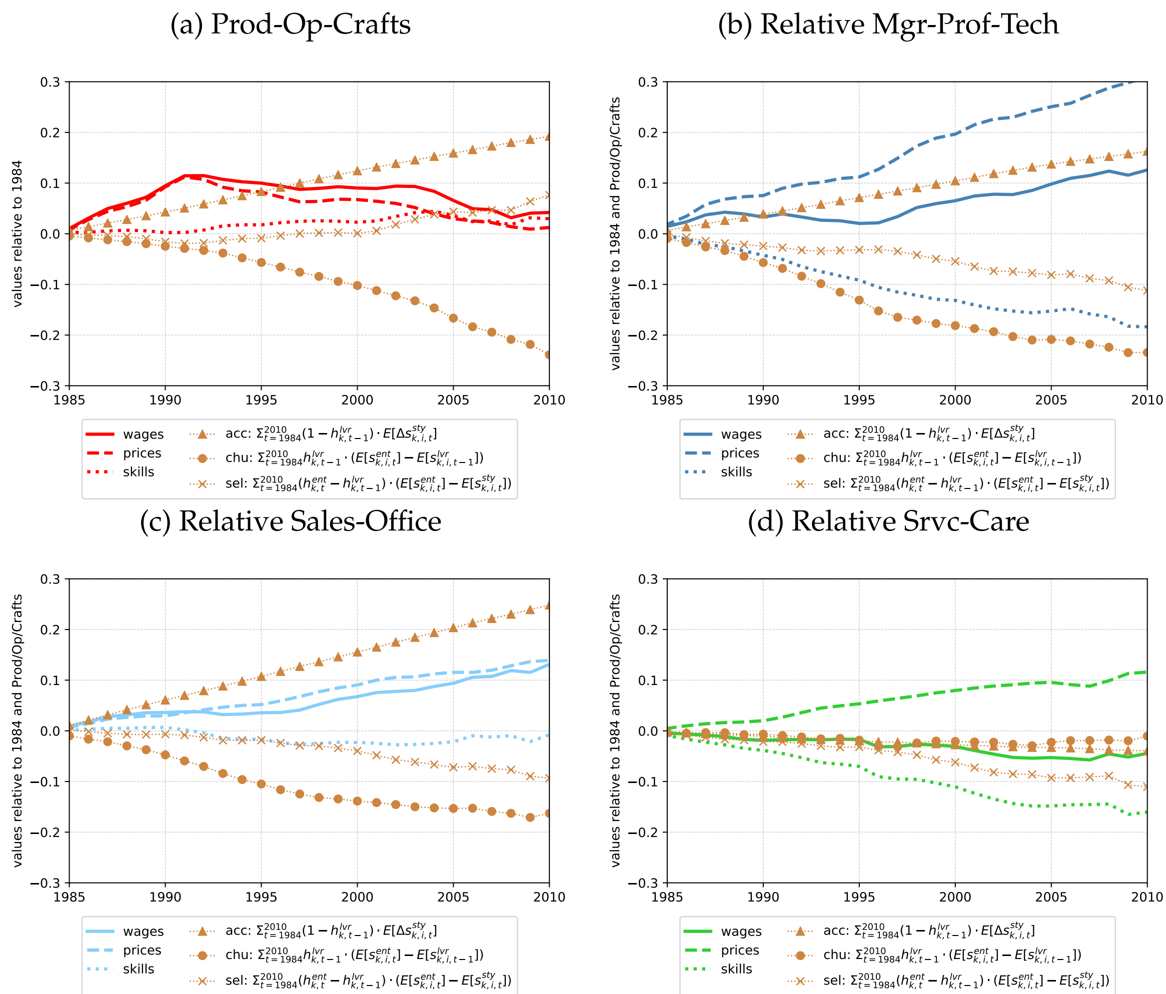
ous section, that is, that average sectoral wages did not polarize despite polarizing task prices because of negative skill selection into the rising sectors. This is consistent with the notion from the Roy model that marginal workers, those who leave or enter a sector when it is shrinking or growing, respectively, may be less skilled than staying (or incumbent) workers.[16] It is also reflected in the substantially lower wages of entering and leaving workers compared to incumbents or stayers reported in Figure 2 and Table A4. Therefore, skills in growing sectors may become more negatively selected *because of* their rising employment and vice versa for skills in shrinking sectors.

The evidence on task prices, sector growth, and skill selection for detailed occupations from the last section underscored this hypothesis. In particular, Figure 5c showed that there is a significant negative relationship between employment growth and implied skill selection even within 120 detailed occupations. Notice also that employment growth itself is not used in our estimation and that the direct relationship between task price growth and skill selection is even more strongly negative (not plotted for brevity).

[16]McLaughlin and Bils (2001) and Young (2014), among others, show that this is the case when workers' comparative and absolute advantages are sufficiently correlated. Our skill accumulation estimates imply that this correlation strengthens for a given worker within his chosen profession over time.

To further investigate this relationship for our four professions, it is again most informative to plot the three components of (10) relative to a reference sector, as it removes effects due to aggregate productivity or skill changes. This is shown in the colored main series of Figure 7, with the absolute values for Prod-Op-Crafts and relative for the three other professions. We indeed see in Figure 7 that for all three professions with rising relative task prices skill selection (dotted line) is negative, though weakly so for Sales-Office, and pulling down average wages (solid). This is substantially attenuating wage growth for Mgr-Prof-Tech and even overturning the effect of the task prices in the case of the low-earning Srvc-Care profession.

Figure 7: Decomposition of Skills into Accumulation, Churning, and Selection



Source: SIAB data, own calculations. The colored main series in the top left panel shows average wages, cumulative task prices, and the difference between two (i.e. the skill composition) of the production and crafts profession over time. The remaining panels show these same variables *relative to* Prod-Op-Crafts. The brown dashed and dotted series show Equation (11)'s further decomposition of professions' skills into effects due to accumulation, churning, and marginal selection. Find the absolute values of all professions in Appendix Figure A19.

The strong selection effects in these rising professions (and the rising detailed occupations of Figure 5c) could stem from a variety of sources. It is therefore useful to separate out the effect of the above-discussed lower skills of marginal workers from other factors that may have driven the four professions' relative skill composition. We split the change in mean skills from Equation (10) into three components:

$$\begin{aligned}\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = &\underbrace{\left(1-h^{lvr}_{k,t-1}\right)\cdot \mathrm{E}[\Delta s^{sty}_{k,i,t}]}_{\text{1 \textbf{learn}ing: accumulation of stayers}} \\ &+\underbrace{h^{lvr}_{k,t-1}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\text{2 \textbf{churn}ing: difference entrants, leavers}} \\ &+\underbrace{\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{sty}_{k,i,t}]\right)}_{\text{3 \textbf{marg}inal \textbf{sel}ection}}\end{aligned} \tag{11}$$

Here, superscript sty indicates a profession stayer, lvr a leaver, and ent an entrant. $h^{lvr}_{k,t-1}$ indicates the share of last period's workers in k who left the profession in this period and $h^{ent}_{k,t}$ the share of this period's workers who entered this period.[17] An alternative decomposition based on the marginal selection of leavers and the corresponding figures are in Appendix D.2.

We can see from the decomposition that if skill accumulation $\mathrm{E}[\Delta s^{sty}_{k,i,t}]$ in a profession k is high, as in Mgr-Prof-Tech and Sales-Office according to our estimates, this raises the first term in Equation (11). But at the same time it also tends to lead to a large (negative) difference in skills $\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)$ between entrants and leavers

[17] Formally, the components are defined as

$$\begin{aligned}&\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = \Big[\underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1,I_{k,i,t-1}=1]}_{\mathrm{E}[s^{sty}_{k,i,t}]}\underbrace{P(I_{k,i,t-1}=1|I_{k,i,t}=1)}_{1-h^{ent}_{k,t}} \\ &+\underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1,I_{k,i,t-1}=0]}_{\mathrm{E}[s^{ent}_{k,i,t}]}\underbrace{P(I_{k,i,t-1}=0|I_{k,i,t}=1)}_{h^{ent}_{k,t}}\Big]-\Big[\underbrace{\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1,I_{k,i,t}=1]}_{\mathrm{E}[s^{sty}_{k,i,t-1}]} \\ &\times\underbrace{P(I_{k,i,t}=1|I_{k,i,t-1}=1)}_{1-h^{lvr}_{k,t-1}}+\underbrace{\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1,I_{k,i,t}=0]}_{\mathrm{E}[s^{lvr}_{k,i,t-1}]}\underbrace{P(I_{k,i,t}=0|I_{k,i,t-1}=1)}_{h^{lvr}_{k,t-1}}\Big]\end{aligned}$$

The intermediate steps for (11) are $\mathrm{E}[(1-h^{ent}_{k,t})s^{sty}_{k,i,t}+h^{ent}_{k,t}s^{ent}_{k,i,t}]-\mathrm{E}[(1-h^{lvr}_{k,t-1})s^{sty}_{k,i,t-1}+h^{lvr}_{k,t-1}s^{lvr}_{k,i,t-1}] =$

$= (1-h^{lvr}_{k,t-1})\mathrm{E}[\Delta s^{sty}_{k,i,t}]+\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\mathrm{E}[s^{sty}_{k,i,t}]+h^{lvr}_{k,t-1}\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)+\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\mathrm{E}[s^{ent}_{k,i,t}]$.

and the deteriorating impact of churning (second term of (11)) on average skills will be strong. High turnover of workers in the profession $h^{lvr}_{k,t-1}$ is negative for the first as well as the second term.

Both the accumulation and the churning effect are unrelated to the profession's growth or decline. In a 'steady state' of the profession in the sense that task prices, employment, and skill composition are constant, they should in fact cancel each other out as the skill accumulation of staying workers makes up exactly the difference in skills between entrants and leavers. We see in all four panels of Figure 7 that the golden lines with triangle and dot markers indeed approximately sum to zero in every year.

Therefore, the changes in sectors' skill composition should largely be due to the third term of Equation (11), marginal selection, which is directly related to sector growth. The marginal selection effect consists of the difference in skills between profession entrants and stayers $\mathrm{E}[s^{ent}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t}]$ and net entry $h^{ent}_{k,t} - h^{lvr}_{k,t-1}$. The skill difference is strongly negative for all professions according to relative wages reported in Figure 2 above, while net entry is positive for growing and negative for shrinking sectors. We see in Figure 7 that this marginal selection effect explains a substantial part of the overall change in the skill composition of the Mgr-Prof-Tech and Srvc-Care professions, and it is stronger than the overall change in relative skill composition for the Sales-Office profession.

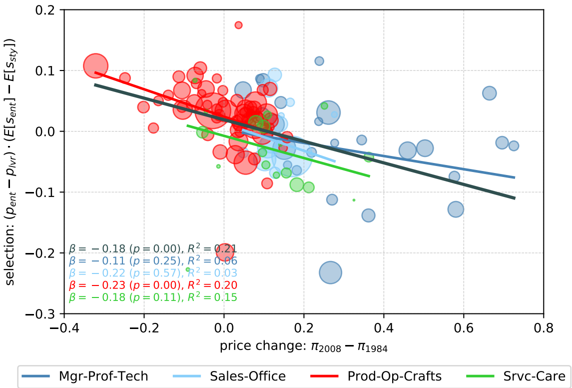
Notice that the marginal selection effect does not depend on the estimated task prices; we empirically implement the skill difference $\mathrm{E}[s^{ent}_{k,i,t-1}] - \mathrm{E}[s^{sty}_{k,i,t-1}]$ by using wages $\mathrm{E}[w^{ent}_{k,i,t-1}] - \mathrm{E}[w^{sty}_{k,i,t-1}]$. Its trending with the implied skill selection therefore provides independent evidence supporting the plausibility of our estimates. In addition, the marginal selection effect is *due to* sector growth. It is exactly zero when employment in profession k is constant, positive when employment declines, and negative when it rises because the skill difference between entrants (or leavers) and profession incumbents is always negative in the data.

Before continuing we check the robustness of this result. The marginal selection effect from the alternative decomposition shown in Appendix D.2 is slightly weaker than in Equation (11). Therefore, an "average decomposition" (formally in Appendix D.2) would come to the conclusion that the marginal selection effect more than fully explains the changing relative skill composition of the Sales-Office profession and more than half of the changing relative skill composition of Mgr-Prof-Tech and Srvc-Care. Of course, the implied skill selection and the marginal selection effect do not have to match perfectly since other factors also change over time.[18] In addition, the decomposition makes a sharp (and potentially unrealistic) distinction between entrants in the current period and incumbents who have just entered the profession one period ago. Nonetheless, it suggests that differences in wages of entrants versus incumbents are qualitatively as well as quantitatively consistent with the strong selection effects implied by our estimation.

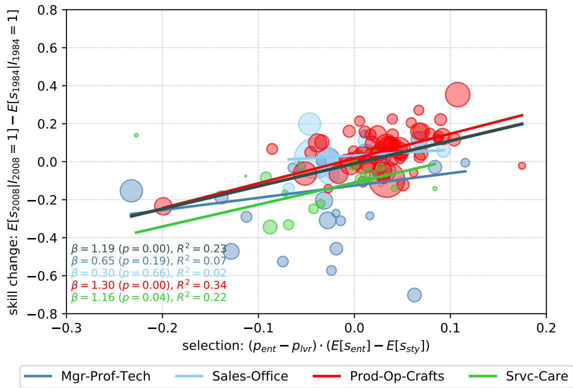
Figure 8 shows the results of this exercise for all 120 occupations. For instance, the two upper panels show the final values of the selection effect in 2008 against price changes and skill changes, respectively. Clearly, a price increase is correlated with a negative selection effect (Figure 8a). In turn, the more negative the selection effect is, the more the average still within an occupation declined over time (Figure 8b).

Figure 8: Marginal Selection, Price and Skill Growth

(a) Prices and Selection



(b) Selection and Skills



Source: SIAB data, own calculations. One bubble in the graphs represents one of the 120 occupations in the SIAB data. The size of one bubble is proportional to the number of workers within one occupation. The colored lines were fitted within the respective four professions. P-values are in parentheses.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Our final step in this section investigates the sources of the marginal selection effect

[18]For example, the more extreme churning effect in Prod-Op-Crafts after the mid-1990s (because of declining relative wages of entrants in that profession, see Figure A20) leads to a more positive relative churning effect in the other three professions. In the case of Sales-Office this almost exactly compensates the marginal selection effect so that overall skill selection hardly changes.

in order to understand its economic mechanism. First, we decompose the contributions of sector switchers, entrants from unemployment or out of the labor force during their careers, and from new labor market entrants. That is, one can rewrite the average skills of entrants as:

$$\mathrm{E}[s^{ent}_{k,i,t}] = h^{ent,swt}_{k,t}\mathrm{E}[s^{ent,swt}_{k,i,t}] + h^{ent,unem}_{k,t}\mathrm{E}[s^{ent,unem}_{k,i,t}] + h^{ent,olf}_{k,t}\mathrm{E}[s^{ent,olf}_{k,i,t}] + h^{ent,new}_{k,t}\mathrm{E}[s^{ent,new}_{k,i,t}] \tag{12}$$

where the shares of entrants who are profession switchers $h^{ent,swt}_{k,t}$, entering from unemployment $h^{ent,unem}_{k,t}$ or out of the labor force during their careers $h^{ent,olf}_{k,t}$, and new labor market entrants $h^{ent,new}_{k,t}$ sum to one. Then we plot the contributions of these groups to the marginal selection effect for each profession *relative* to Prod-Op-Crafts in the left panels of Figure 9.[19]

Second, we examine to what extent the differences in skills between incumbents and entrants reflect endowments upon entering the sector versus skill accumulation since entering. We compute the skills that incumbents accumulated since they joined the sector $x_{i,t}$ periods ago from the growth in their observed wages:

$$s^{sty}_{k,i,t-x_{i,t}} - s^{sty}_{k,i,t} = w_{k,i,t-x_{i,t}} - w_{k,i,t} + \hat{\pi}_{k,t-x_{i,t}} - \hat{\pi}_{k,t} \tag{13}$$

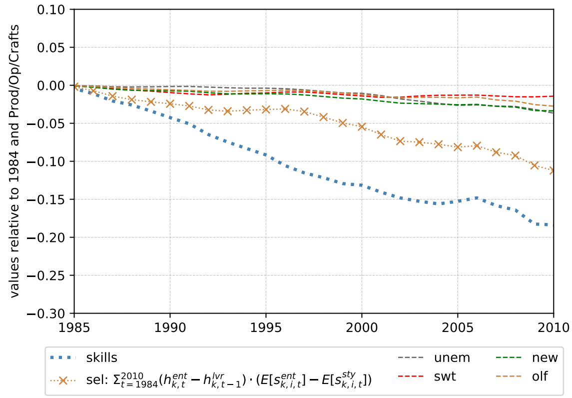
We then plot the marginal selection component from Equation (11) that is due to differences at entry $\left(h^{ent}_{k,t} - h^{lvr}_{k,t-1}\right)\left(\mathrm{E}[s^{ent}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t-x_{i,t}}]\right)$ versus the differences that are due to skill accumulation $\left(h^{ent}_{k,t} - h^{lvr}_{k,t-1}\right)\left(\mathrm{E}[s^{sty}_{k,i,t-x_{i,t}} - s^{sty}_{k,i,t}]\right)$ for each profession in the respective right panels of Figure 9.

We can see in the left panels of Figure 9 that, while switchers from other professions also contribute, most of the negative marginal selection effect is due to entrants from unemployment, out of the labor force, and new workers in the labor market, especially in the services sector. This result is consistent with such workers' skills and thus their wages being substantially below incumbents in all of the professions, and especially

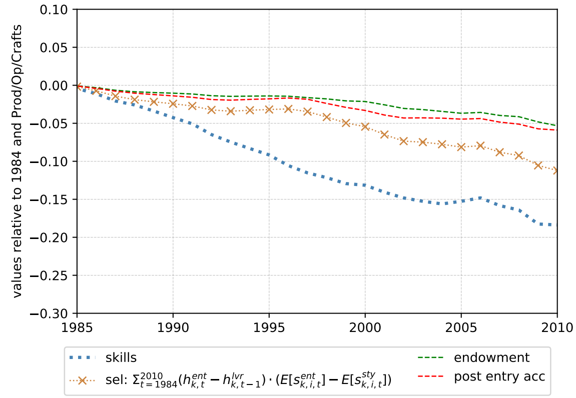
[19]Formally, these contributions are $\left(h^{ent}_{k,t} - h^{lvr}_{k,t-1}\right) h^{ent,swt}_{k,t}\left(\mathrm{E}[s^{ent,swt}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t}]\right)$, $\left(h^{lvr}_{k,t-1} - h^{ent}_{k,t}\right) h^{ent,unem}_{k,t}\left(\mathrm{E}[s^{ent,unem}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t}]\right)$, $\left(h^{ent}_{k,t} - h^{lvr}_{k,t-1}\right) h^{ent,olf}_{k,t}\left(\mathrm{E}[s^{ent,olf}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t}]\right)$, and $\left(h^{ent}_{k,t} - h^{lvr}_{k,t-1}\right) h^{ent,new}_{k,t}\left(\mathrm{E}[s^{ent,new}_{k,i,t}] - \mathrm{E}[s^{sty}_{k,i,t}]\right)$.

Figure 9: Decomposition of the Marginal Selection Effect

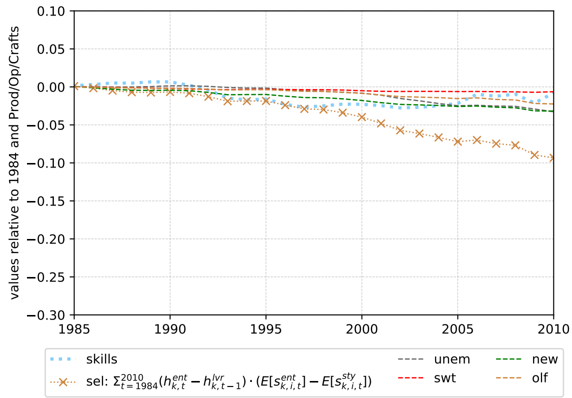
(a) Groups - Mgr-Prof-Tech



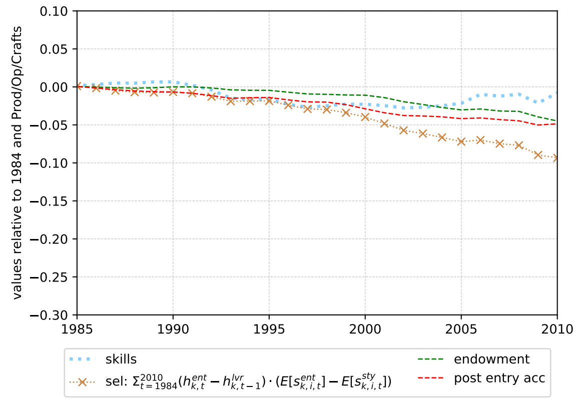
(b) Acc vs Ent - Mgr-Prof-Tech



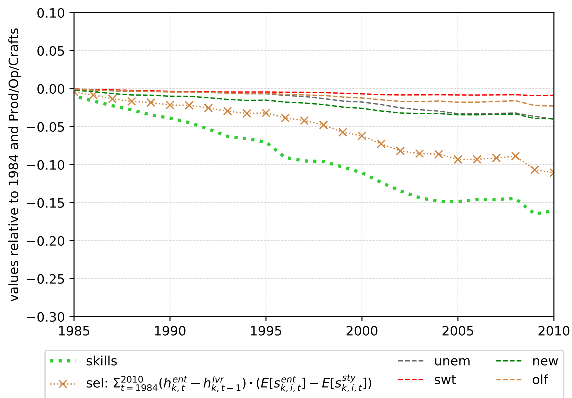
(c) Groups - Sales-Office



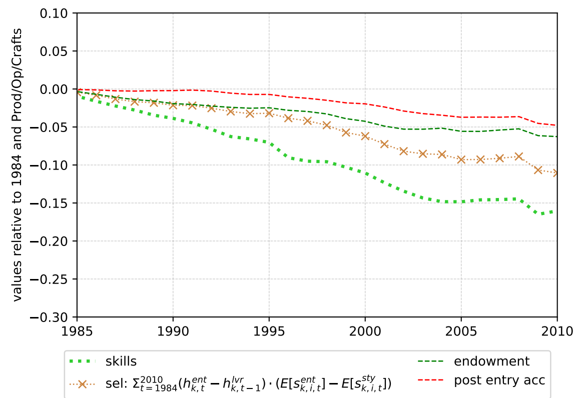
(d) Acc vs Ent - Sales-Office



(e) Groups - Srvc-Care



(f) Acc vs Ent - Srvc-Care



Source: SIAB data, own calculations. The lefts panels show the decomposition of the marginal selection effect into the groups: unemployed, out of labor force, switchers and new labor market entrants as given by Equation (12). The right panels plot the decomposition parts of the marginal selection effect into the influence of differences in skill endowment and skill accumulation over time as given by Equation (13) and the following.

in services (see Table A14).

The right panels of Figure 9 reveal that a majority of the marginal selection effect and thus the skill differences between entrants and incumbents in high-skill Mgr-Prof-Tech and Sales-Office professions is due to skill accumulation. That is, the decomposition (13) shows that, while new entrants are less skilled than incumbents already at entry into the profession, the majority of the skill differences are due to the skill accumulation from which the latter benefitted. This finding is consistent with the high rate of skill accumulation in Mgr-Prof-Tech and Sales-Office depicted in Figure 6 and it underscores the argument we make throughout this paper that skill accumulation is important for understanding strong selection effects into evolving sectors. Therefore, fixed effects or cross-sectional estimates of these selection effects may be misleading.

In the case of Srvc-Care professions, bottom right panel of Figure 9, the effect due to skill accumulation is again strong. However, it is smaller than the differences in skill endowments, which are even stronger because of the large contribution of very low-skill marginal entrants from unemployment, out of the labor force, and new workers in the labor market discussed above. Appendix D.2 shows an alternative estimate to Equation (13) of the marginal selection effect due to endowments versus skill accumulation of stayers.[20] Though somewhat less important, the skill accumulation component still explains half of the marginal selection effect in Mgr-Prof-Tech and Sales-Office and a non-negligible part in Srvc-Care.

We conclude from this analysis that the net entry of substantially lower-skilled workers leads to negative selection effects into the growing professions in our data. These selection effects are independent of the task price estimates and so substantial that they can explain most of the strongly deteriorating skill composition implied by the estimates. Moreover, different skill endowments of incumbents versus entrants into sectors by themselves are insufficient to account for the selection effects. Instead, a large part of them are the skill accumulation of incumbents that occurred during the years they have worked in the respective profession.

Therefore, to summarize, the empirical results of the last two sections are consistent

[20] In the respective Figure A17 we use only the estimated systematic accumulation ($s^{sty}_{k,i,t} - s^{sty}_{k,i,t-x_{i,t}} = \sum_{\tau=1}^{x_{i,t}} \sum_{a=1}^{A} I_{k,i,t-\tau} \cdot \mathbb{1}[\text{age}_{i,t-\tau} \in a] \cdot \hat{\gamma}_{k,k,a}$) and thus exclude idiosyncratic shocks.

with increased demand, e.g. due to RBTC, driving task prices and employment of certain (groups of) occupations. However, employment growth is at the same time a force for deteriorating selection into the rising occupations via lower permanent and accumulated skills of net entrants. Since the two forces largely cancel each other out, average wage growth is not in general related to rising demand or task prices for occupations, with even qualitatively misleading results as in the Srvc-Care profession of our analysis. Therefore, we need to estimate the task prices to correctly interpret demand versus supply shifts for occupations, to obtain the changing skill selections, and to conduct meaningful counterfactual analyses, which we do in the next section.

6 Task Prices, Skill Selection, and the Wage Distribution

How would the wage inequality have changed had task prices not changed? How would the wage distribution have evolved if workers had not switched professions thereby gaining or loosing from changing prices? What would have been the result if workers' skills were constant over the life cycle so that selection due to changing prices would not have led to changes in average skill accumulation by wage percentile?

Answering these questions requires counterfactual simulations which enable us to link changes in the returns to profession specific skills and changes in the overall wage distribution. In this section, we use our estimates for task price changes and life cycle skill accumulation as well as workers' changing allocation across professions to evaluate how German wage inequality would have changed if only these factors or subsets thereof had influenced the wage distribution.

As we do not have much to say about workers' skills (and thus wages) at labor market entry, we focus on the influence of changing prices and skill accumulation during the career.

The dark brown lines use our estimates for task prices and skill accumulation to predict log wages for each individual after labor market entry at time $t_{\text{ent}(i)} < t$ and last observed spell $x_{i,t}$ periods ago:[21]

$$\hat{w}^c_{i,t} = w_{i,t_{\text{ent}(i)}} + \sum_{k}^{K} \sum_{\tau=t_{\text{ent}(i)}+1}^{t} I_{k,i,t} \Delta\hat{\pi}_{k,\tau} + \sum_{k}^{K} \sum_{k'}^{K} \sum_{\tau=t_{\text{ent}(i)}+1}^{t} \bar{I}_{k,i,\tau} I_{k',i,\tau-x_{i,t}} \hat{\gamma}_{k',k,a} \tag{14}$$

Employing the predicted wages, we then compute the standard deviation of log wages and percentiles of the predicted wage distribution which are "due to the model". By construction, predicted and observed wages at age 25 are equal for all cohorts. The dark brown lines in the left panels are again increasing and the slope is slightly rising over time. However, the fit becomes worse and worse over the life cycle due to idiosyncratic wage changes – skill shocks through the lense of the model – which are responsible for a substantial fraction (ca 40% at age 54) of the dispersion in life cycle trajectories. In particular, a worker might only be able to reach the very upper part of the wage distribution via a positive idiosyncratic skill shocks whereas he might only reach very lower parts through negative shocks. The right panels show that this is exactly what is going on. The model underpredicts the rise in the 85th percentile but overpredicts the rise in the 15th percentile so that the simulated inequality is smaller for all ages than the actual.

The gray lines then go one step further by fixing the profession of a worker to be his initial profession. Hence, counterfactual wages are predicted as:

$$\hat{w}^c_{i,t} = w_{i,t_{\text{ent}(i)}} + \sum_{k}^{K} \sum_{\tau=t_{\text{ent}(i)}+1}^{t} I_{k,i,t_{\text{ent}(i)}} \Delta\hat{\pi}_{k,\tau} + \sum_{k}^{K} \sum_{\tau=t_{\text{ent}(i)}+1}^{t} \bar{I}_{k,i,t_{\text{ent}(i)}} I_{i,\tau-1} \hat{\gamma}_{k,k,a} \tag{15}$$

where $I_{i,\tau-1}$ indicates if i is in the labor force at $\tau - 1$. Turning off switches during the career leads to a slightly flatter life-cycle increase in the standard deviation of wages but relatively large effects for the 85th percentile. For instance, if switching had not been possible for the cohort born between 1960 and 1964, the 85th percentile would have increased by €5,000 less than in the full model (€65,000 compared to €60,000 at age 54). This implies switching is a substantial component of wage growth over the

[21] As workers can have breaks between two employment spells, e.g. becoming unemployed, $x_{i,t}$ can be different from one. Thereby, we implicitly assume that skill do not change during these spells. As in the estimation, switchers receive the conditional mean change in wages from switching.

life cycle that has become more important over time, especially for the 85th percentile of the wage distribution.

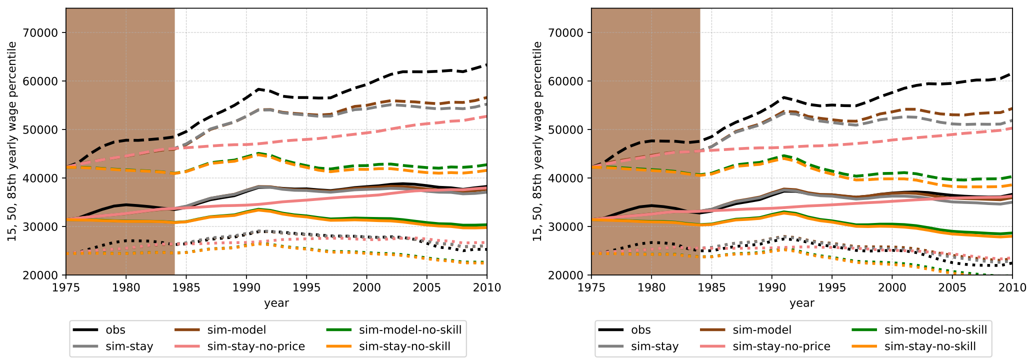
The effect of switching, in turn, can have two sources: (1) the increasing prices in Mgr-Prof-Tech and Sales-Office (as well as Srvc-Care) and (2) differences in skill accumulation between professions with increasing and decreasing task prices. To explore these sources, we now set price changes and skill accumulation, respectively, to zero and recompute the inequality measures with these newly predicted counterfactual wages. The pink line shows the results for price changes set to zero so that only skill accumulation leads to increasing wages over the life cycle, as workers can neither gain by switching nor through price increases which occur in their existing professions. In turn, the orange line depicts how wage inequality would change if workers could not accumulate skills but only profit or loose from changing task prices. In sum, the lines show that changing task prices can roughly account for a third of the rise in inequality over the life cycle whereas skill accumulation accounts for the remaining two thirds. If task prices change, employment polarizes so that former production workers go into Mgr-Prof-Tech. This leads to changes in the average skill accumulation for a certain percentile of the wage distribution, as Mgr-Prof-Tech workers have higher skill growth.

How much of the change in overall inequality can be explained by our model? How would the overall wage distribution have evolved over the years if task prices had not changed or if there was no skill accumulation? To see this, Figure 10 repeats the exercise from above for each year pooled over all ages and birth cohorts in the top row. Again, the model underpredicts the rise in inequality over the years mainly because of the smaller increase in the upper part of the wage distribution. If switching is shut down, the rise in inequality is even lower, mostly because of a smaller increase in the 85th percentile and a larger increase of the 15th percentile. Setting skill growth to zero, leads to an almost constant wage distribution or even slightly narrowing inequality. This is likely due to lower entry wages or declining Prod-Op-Crafts task prices. In contrast, setting price changes to zero still lets the wage distribution get more dispersed over time due to differences in skill accumulation in conjunction with job polarization, since more Mgr-Prof-Tech workers are found in the 85th percentile than in the 50th or

15th percentile. Hence, both changing task prices through its impact on selection as well as differences in skill accumulation between professions whose returns change differently are responsible for the rise in German inequality.

Figure 10: Counterfactual Changes of the Wage Distribution by Years

(a) Baseline sample (b) Filled non employment



Source: SIAB data, own calculations. The panels show the 15th, 50th and 85th percentiles of the wage distribution by year. The predicted (counterfactual) values were computed according to Equation (14) for the sim-model and sim-model-no-skill line as well as Equation (15) for sim-stay, sim-stay-no-price and sim-stay-no-skill. The left panel uses the baseline sample data. The right panel was created using the sample where non employment spells were filled up as described in the text. Price and skill accumulation estimates were received from the baseline specification with four professions.
Legend: obs: observed; sim-model: simulated using switching, prices, accumulation; sim-stay: simulated using prices, accumulation; sim-stay-no-price: simulated using accumulation; sim-stay-no-skill: simulated using prices. The shaded area represents years in the base period.

Lastly, we assess what impact the decrease in unemployment rates had on the wage structure. It is often argued that the reduction in German unemployment rates was achieved at the expense of an increase in wage inequality, especially at the bottom of the wage distribution (Dustmann et al., 2014). The bottom row of Figure 10 shows the evolution of the wage percentiles for the sample where we filled up unemployment and out of labor force spells with the lower wage of the two adjacent employment spells as in Section D.1.2. The intuition for this is that workers could always take the lower-paying job instead of becoming unemployed. As the unemployment rate has fallen over time, we fill up fewer and fewer spells with those low wages over time. In fact, workers may have exchanged their unemployment with low-paying jobs themselves. For instance, the introduction of the Hartz Reforms in 2004 may have forced them to do so by its reduced benefits or its introduction of conditional unemployment benefits. Therefore, the exercise essentially simulates how the German wage distribution would have changed had workers always been forced to take up low-paying jobs and not just after 2004.

Indeed, comparing the change in simulated percentiles (sim-model) between 2004 and 2010 for filled up and non filled up spells shows no differences, making us confident that this approach correctly simulates that after 2004 workers had to take up more low-paying job offers. What would have been the effect on inequality prior to 2004 if workers had always had to do that? The answer to this can be found by comparing percentiles between the left and right graph. Most strikingly, the model overpredicts the rise in the 85th percentile if one fills up non employment spells which is likely to be due to an improvement in skill accumulation as workers now stay within the labor market for longer. In contrast, the 15th percentile for filled up spells is now below the one simulated for non filled up spells which can be explained by greater selection responses as workers now have to take up lousy jobs earlier than they might do in reality where they may want to wait for better offers longer. Hence, the rise in inequality would have been greater, supporting the view that the decline in unemployment was bought at the price of greater inequality. Nevertheless, this is mainly because of greater skill accumulation which may benefit everyone, especially the long term unemployed. An overall welfare analysis is beyond the scope of this paper.

7 Conclusion

It has long been recognized based on Roy theory that marginal entrants into a given sector may be less skilled than inframarginal incumbents (e.g. McLaughlin and Bils, 2001; Young, 2014). It has also been argued that changes in observed average wages may not be informative about the labor demand or supply shocks affecting different sectors because of skill composition effects (Heckman and Sedlacek, 1985; Böhm, 2017). In this paper, we develop a new method for estimating changes in task prices, that is, selection-corrected wage rates, for potentially many sectors in longitudinal data. The method exploits information about individual workers' sector choices and associated wage growth, which according to Roy theory should be closely linked via task prices. Other strengths of the method include that it is easy to implement, transparent in which moments are used for identification, and that it does not require specific assumptions about the distribution of workers' skills or their changes. We conduct extensive Monte Carlo simulations to validate the method and a battery of robustness checks for the empirical results. We also analyze the validity of the approach under various extensions of the underlying economic model.

The empirical results from this new method highlight that sectors' task prices, employment changes, and skill selection interact in systematic and important ways. In particular, the positive correlation between employment and task price growth implies that (relative) labor demand rather than supply shocks are the dominant drivers of changes in occupational outcomes. This correlation does not carry over to the observed wages because skill selection strongly deteriorates in rising sectors, which offsets the increasing task prices. In fact, negative selection is closely linked to employment growth across occupations via net entry of marginal workers. These entrants are less skilled than incumbents not only because of lower initial endowments but equally importantly because of incumbents' prior (sector-specific) skill accumulation. The skill accumulation effect has not been widely recognized in previous work, likely because fixed effects or cross-sectional estimations focus on skill differences that are time-invariant or fixed at a given point in time, respectively. To our knowledge, this study is therefore the first to systematically identify and empirically quantify this effect.

There a several promising avenues for future research that may emanate from this study. First, it would be fruitful to be able to describe the joint population distribution of skill endowments and accumulation that results from our estimation. This would enable quantification of labor supply elasticities to different sectors and it would allow much richer counterfactual analyses than the one in this paper. For example, what would happen to the (sectors of) employment and wage outcomes of Mgr-Prof-Tech workers when the task prices for some of these sub-professions were starting to decline (e.g. because of the impact of artificial intelligence)? The estimation method could also be applied or extended to apply to other settings such as continuous task measures, industries instead of occupations to study structural transformation, and, most intriguingly, to the burgeoning research on the role of firms in the wage structure. In particular, identification of fixed effects in that literature requires a conditional exogeneity assumptions for workers' transitions between firms, which may be critically violated in practice. If it is possible to extend our method to estimate changing "task prices" for firms, i.e. firm effects that allow for endogenous worker switching, this could be an important check for the validity of the results from double fixed effect estimations. It would also provide an even more fine-grained picture of the role of task prices for the changes in wage inequality over the last decades.

References

ACEMOGLU, D. AND D. H. AUTOR (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics, vol. 4 Part B*, ed. by D. Card and O. Ashenfelter, Elsevier, chap. 12, 1043–1171.

ALTONJI, J. G. AND C. R. PIERRET (2001): "Employer learning and statistical discrimination," *The Quarterly Journal of Economics*, 116, 313–350.

ARELLANO, M. AND S. BOND (1991): "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies*, 58, 277–297.

ARTUÇ, E. AND J. MCLAREN (2015): "Trade policy and wage inequality: A structural analysis with occupational and sectoral mobility," *Journal of International Economics*, 97, 278–294.

AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): "The China syndrome: Local labor market effects of import competition in the United States," *The American Economic Review*, 103, 2121–2168.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118, 1279–1333.

BLINDER, A. S. AND A. B. KRUEGER (2013): "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics*, 31, S97–S128.

Böhm, M. (2017): "The Price of Polarization: Estimating Task Prices Under Routine-Biased Technical Change," Working Paper.

Bowlus, A. J. and C. Robinson (2012): "Human Capital Prices, Productivity, and Growth," *American Economic Review*, 102, 3483–3515.

Card, D., J. Heining, and P. Kline (2013): "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 128, 967–1015.

Carrillo-Tudela, C., B. Hobijn, P. She, and L. Visschers (2016): "The extent and cyclicality of career changes: Evidence for the U.K." *European Economic Review*, 84, 18 – 41, european Labor Market Issues.

Cavaglia, C. and B. Etheridge (2017): "Job Polarization, Task Prices and the Distribution of Task Returns," Working Paper.

Chetty, R. (2009): "Sufficient Statistics for Welfare Analysis: A Bridge between Structural and Reduced-Form Methods," *Annual Review of Economics*, 1, 451–488.

Combes, P.-P., G. Duranton, and L. Gobillon (2008): "Spatial wage disparities: Sorting matters!" *Journal of Urban Economics*, 63, 723–742.

Cortes, G. M. (2016): "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data," *Journal of Labor Economics*, 34, 63–105.

Cortes, G. M. and G. Gallipoli (2017): "The costs of occupational mobility: An aggregate analysis," *Journal of the European Economic Association*, jvx006.

Dix-Carneiro, R. (2014): "Trade liberalization and labor market dynamics," *Econometrica*, 825–885.

Dustmann, C., B. Fitzenberger, U. Schönberg, and A. Spitz-Oener (2014): "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy," 28, 167–188.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009): "Revisiting the German wage structure," *Quarterly Journal of Economics*, 124, 843–881.

FINKELSTEIN, A., N. HENDREN, AND E. F. LUTTMER (2015): "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment," Tech. Rep. 21308, National Bureau of Economic Research.

FIRPO, S., N. M. FORTIN, AND T. LEMIEUX (2013): "Occupational Tasks and Changes in the Wage Structure," *Working Paper*.

FITZENBERGER, B. (1999): "Wages and Employment Across Skill Groups: An Analysis for West Germany," Tech. rep., Heidelberg: Physica/Springer.

FITZENBERGER, B., A. OSIKOMINU, AND R. VÖLTER (2006): "Imputation Rules to Improve the Education Variable in the IAB Employment Subsample," *Schmollers Jahrbuch(Journal of the Applied Social Sciences)*, 126, 405–436.

GANZER, A., A. SCHMUCKER, P. VOM BERGE, AND A. WURDACK (2017): "Sample of Integrated Labour Market Biographies Regional File 1975-2014 (SIAB-R 7514)," Tech. Rep. 1, FDZ–Datenreport.

GATHMANN, C. AND U. SCHÖNBERG (2010): "How General is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 28, 1–49.

GIBBONS, R., L. F. KATZ, T. LEMIEUX, AND D. PARENT (2005): "Comparative advantage, learning, and sectoral wage determination," *Journal of labor economics*, 23, 681–724.

GIBBONS, R. AND M. WALDMAN (1999): "A Theory of Wage and Promotion Dynamics Inside Firms*," *The Quarterly Journal of Economics*, 114, 1321–1358.

GOOS, M. AND A. MANNING (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89, 118–133.

GOOS, M., A. MANNING, AND A. SALOMONS (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104, 2509–2526.

Gottschalk, P., D. A. Green, and B. M. Sand (2015): "Taking Selection to Task: Bounds on Trends in Occupational Task Prices for the U.S., 1984-2013," Working Paper.

Green, D. A. and B. M. Sand (2015): "Has the Canadian labour market polarized?" *Canadian Journal of Economics*, 48, 612–646.

Heckman, J. J., L. Lochner, and C. Taber (1998): "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1, 1–58.

Heckman, J. J. and G. Sedlacek (1985): "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market," *Journal of Political Economy*, 93, pp. 1077–1125.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2013): "The Allocation of Talent and U.S. Economic Growth," Working Paper 18693, NBER.

Kambourov, G. and I. Manovskii (2009): "Occupational specificity of human capital," *International Economic Review*, 50, 63–115.

Lagakos, D., B. Moll, T. Porzio, N. Qian, and T. Schoellman (2018): "Life-cycle wage growth across countries," *Journal of Political Economy*.

Mazzolari, F. and G. Ragusa (2013): "Spillovers from high-skill consumption to low-skill labor markets," *Review of Economics and Statistics*, 95, 74–86.

McLaughlin, K. J. and M. Bils (2001): "Interindustry mobility and the cyclical upgrading of labor," *Journal of Labor Economics*, 19, 94–135.

Mishel, L., H. Shierholz, and J. Schmitt (2013): "Don't Blame the Robots: Assessing the Job Polarization Explanation of Growing Wage Inequality," *EPI Working Paper*.

Naticchioni, P., G. Ragusa, and R. Massari (2014): "Unconditional and Conditional Wage Polarization in Europe," *IZA Discussion Paper*.

POLETAEV, M. AND C. ROBINSON (2008): "Human capital specificity: evidence from the dictionary of occupational titles and displaced worker surveys, 1984–2000," *Journal of Labor Economics*, 26, 387–420.

SOLON, G., R. BARSKY, AND J. A. PARKER (1994): "Measuring the cyclicality of real wages: how important is composition bias?" *The quarterly journal of economics*, 109, 1–25.

SPITZ-OENER, A. (2006): "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure," *Journal of Labor Economics*, 24, 235–270.

VON GAUDECKER, H.-M. (2014): "Templates for Reproducible Research Projects in Economics," `https://github.com/hmgaudecker/econ-project-templates`.

YAMAGUCHI, S. (2012): "Tasks and Heterogeneous Human Capital," *Journal of Labor Economics*, 30, 1–53.

——— (2016): "Changes in returns to task-specific skills and gender wage gap," *Journal of Human Resources*, 1214–6813R2.

YOUNG, A. (2014): "Structural transformation, the mismeasurement of productivity growth, and the cost disease of services," *The American Economic Review*, 104, 3635–3667.

Appendix

A Dataset Construction

This study uses the factually anonymous Sample of Integrated Labor Market Biographies (version 7415). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) under contract Number 101357[22]. See Ganzer et al. (2017) for an up to date overview of the data.

Structure: The SIAB is a 2% random sample of administrative social security records from 1975 to 2014. It is representative for 80% of the German workforce and includes employees covered by social security, marginal part-time employment, benefit receipts, officially registered as job-seeking or participating in programs of active labor market policies. It therefore excludes the self-employed, civil servants, individuals performing military service as well persons not in the labor force. Most notably, it contains an individual's full employment history, the occupation, wage, year of birth, place of work and education. The data is exact to the day as employers need to notify the employment agency if the employment relationship changes. This means there can be various employers for an individual worker within a year and those spells can even overlap as workers can have multiple employment contracts at a time. We transform this spell structure into a yearly panel structure by identifying the longest spell (a spell can have length of 365/366 days at most in a year) within a given year and deleting all the remaining spells. This procedure differs from the previous inequality literature (Dustmann et al., 2009, e.g.) which aggregate all the information from various spells within a year. For example, they add up all the earnings from multiple employment spells. Since our focus is on occupations, this is impossible to do as one can not aggregate multiple categorical occupation information. Fortunately, the number of *full time* workers with more than one spell a year is negligible and so of minor concern. However, as spells can last for less than 365/366 days within a year, we weight all observations by their spell duration within a year, e.g. an employee working 140 days in t receives $\omega_{i,t} = 140$ as a weight.

Occupations, education, age: The mapping between (120) occupations and the professions we use in our main analysis, can be found below. Notice, that in our preferred specification we aggregate the ten more detailed professions mentioned in the table below into the four broad groups:

1. Managers-Professionals-Technicians (Mgr-Prof-Tech)
2. Sales-Office (Sales-Office)

[22] You can get access to a *test version* here: `http://fdz.iab.de/en/FDZ_Individual_Data/integrated_labour_market_biographies.aspx`. The full Scientific Use File can only be downloaded after having signed a contract with the FDZ. We carried out all the analyses making use of the templates provided by von Gaudecker (2014). The code is available at `https://gitlab.iame.uni-bonn.de/hmg/task-prices-de` upon request.

3. Production-Operators-Craftsmen (Prod-Op-Crafts)

4. Services-Care (Srvc-Care)

The contained education variable is imputed since it has a lot of inconsistencies and missing values as described in Fitzenberger et al. (2006). From that, we generate an education variable with three possible outcomes: low (without postsecondary education), medium (apprenticeship or Abitur) and high (university or college degree). The age bins used for estimating skill accumulation parameters are $[25, 34], [35, 44], [45, 54]$.

Wage imputations: Despite being accurately measured as the employer can be punished for incorrect reporting, the contained wage variable has two major drawbacks for our analysis. First, wages are top coded, amounting to 12% censored observations for men and 4% censored observations for women on average across years. We impute the wages using the same main method as Card et al. (2013). For this, we perform a series of $2 \cdot 4 \cdot 3 \cdot 40 = 960$ tobit imputations for gender times age ($[21, 34], [35, 44], [45, 54], [54, 60]$) times education (low, medium, high) times year (1975-2014) cells separately to allow for different variances and means across groups and years. We regress the observed, censored log wage on a constant, age (within age groups), the mean wage in other years, the fraction of censored wages in other years as well as a dummy if the person was only observed once in his life[23]. We use the predicted values $X'\hat{\beta}$ from the tobit regressions together with the estimated standard deviation $\hat{\sigma}$ to impute the censored wages y^c as follows: $y^c = X'\hat{\beta} + \hat{\sigma}\Phi^{-1}[k + u(1-k)]$, where $u \sim U[0, 1]$ and $k = \Phi[(c - X'\hat{\beta})/\hat{\sigma}]$ and c is the main censoring limit[24]. We deflate wages with respect to prices as of 2010 and smooth them using three year moving averages. Finally, we multiply them with a factor of 365 to receive yearly wages from daily wages.

Wage break 1983/1984: The second major concern with the wage variable is that the definition of a wage changed from 1983 to 1984. Prior to 1984 wages did not contain bonuses and one time payments. If one does not correct this break, it leads to a spurious increase in inequality between those years when the consistent periods 1975 - 1983 and 1984 - 2014 are not analyzed separately. We deal with this break by correcting wages prior to 1984 upwards following Fitzenberger (1999) and Dustmann et al. (2009). Their idea is that a worker's rank in the wage distribution between 1984 and 1983 should be similar. Additionally, they control for the fact that different percentiles of the wage distribution should be differently affected by the break since workers from higher percentiles are likely to receive higher bonuses. Therefore, they estimate locally weighted regressions of an individual's wage ratio in 1983/1984 and 1983/1982 on the rank of a person in the wage distribution. They then calculate a correction factor as the difference between the predicted, smoothed values from the two wage ratio regressions and multiply wages prior to the break with that factor. After that, some wages are corrected above the censoring limit. Dustmann et al. (2009) reset these wages back to the censoring limit and impute them in the same way they imputed wages which were

[23] If that is the case, the mean wage in other years and the fraction of censored wages in other years is replaced by the sample mean.

[24] Accessible at `http://fdz.iab.de/en/FDZ_Overview_of_Data/working_tools.aspx`.

above the limit anyway. This, however, is very problematic when analyzing wages within high skill professions. For instance, by employing this procedure, the amount of censored wages within the Mgr-Prof-Tech group aged $[45, 54]$ increases from 40% to 80% in 1975. In contrast, there is only a rise from 38% to 50% in 1983. Therefore, the imputation now over-corrects wages the more they date back, which makes imputed and corrected wages of Mgr-Prof-Tech fall between 1975 and 1983, especially for older and more experienced workers. As this is likely to be a problem of the wage break correction approach and not a feature of the data because wages of all other professions increased in that period, we follow a different approach by not imputing wages which were moved above the censoring limit. Instead, we do not reset wages back to the censoring limit if they were corrected above the limit.

Sample selection: The main dataset is restricted to full time working 25 to 54 year old men. Workers without information on the occupation are dropped from the analysis. Additionally, the years 2011 - 2014 are left out as the employment agency's official occupational classification changed in 2011 (KLDB1988 to KLDB2010). A crosswalk exists in the data but is not 1:1 so that a clear break in employment and wages by occupation is observable between 2010 and 2011 and solving it is left for future research. Furthermore, we drop all spells of workers who ever worked in East Germany as well as permanently foreign workers[25]. After that, we are left with 721,953 persons and 8,492,131 person times year combinations. From that, 296,703 persons and 2,703,303 person times year combinations are women so that 425,250 individuals and 5,788,828 person times year combinations are men, which are used for the main estimations.

Imputing unemployment and out of labor force spells: As unemployed persons receive social security benefits, we observe the universe of unemployed persons. If a worker leaves the labor force, however, we do not observe him unless he returns to the labor force. Therefore, we impute out of labor force (olf) spells by filling up all missing years between two employment/unemployment spells in the data[26]. We then drop persons with olf spells longer than 10 consecutive years as prime age men are likely to have switched into the public sector than truly having left the labor force[27]. One of our key robustness checks concerns the role of unemployment and out of labor force spells. As described earlier (see section D.1.3), we relax the exogeneity assumption for unemployment and out of labor force by imputing the profession where the worker "would have worked in had he not become unemployed or left the labor force". We do this imputation by comparing the (real) wage after an unemployment/olf spell with the wage before the unemployment/olf spell. We then impute the wage while in

[25]That is, workers who are German at some point but foreign at another, are not dropped from the sample.

[26]The imputation is done before the sample selection so that we also fill up with out of labor force spells at age 54 in the main specification. That is, the last employment observation can occur during ages > 54.

[27]Between 1996 and 1998, many workers in occupation 102 Physicians until Pharmacists leave the sample and return afterwards as mentioned by Ganzer et al. (2017). We impute those likely erroneously missing observations by setting the occupation to 102 if a worker was in 102 in 1995 and returned in 1999 or 2000 and linearly interpolate the missing wage using the observations in 1995 and 1999/2000.

unemployment/olf as the lower of those two wages adjusted for inflation and set the profession within this time to the profession that corresponds to that lower wage. The rationale for this procedure is based on the idea that a worker could always choose the lower paying job but eventually decides to quit employment if he prefers becoming unemployed. As we only fill up olf spells between two employment or unemployment spells we therefore treat both unemployed persons and persons who permanently left the labor force without returning into employment as exogenous actions. The number of men aged 25 to 54 who permanently leave the labor force is, however, extremely low (1.1%). The imputed sample therefore has no gaps for any person during his first and last observed employment spell. Employing this sample, we then repeat all of the analysis but set the skill accumulation variables to zero if a person is unemployed or out of the labor force. After that, we are left with 789,413 persons and 10,639,100 person times year combinations. From that, 345,544 persons and 3,999,340 person times year combinations are women so that 443,869 individuals and 6,639,760 person times year combinations are men, which are used for the main estimations.

profession	SIAB occupation
Managers	Abgeordnete, Minister, Wahlbeamte bis Verbandsleiter, Funktionaere
	Unternehmensberater, Organisatoren bis Wirtschaftspruefer, Steuerberater
	Unternehmer, Geschaeftsfuehrer, Geschaeftsbereichsleiter
Professionals	Aerzte bis Apotheker
	Architekten, Bauingenieure
	Chemiker, Chemieingenieure bis Physiker, Physikingenieure, Mathematiker
	Datenverarbeitungsfachleute
	Elektroingenieure
	Heimleiter, Sozialpaedagogen
	Hochschullehrer, Dozenten an hoeheren Fachschulen und Akademien bis Fachschul-, Berufsschul-, Werklehrer
	Ingenieure des Maschinen- und Fahrzeugbaus
	Lehrer fuer musische Faecher bis sonstige Lehrer
	Musiker bis Dekorationen-, Schildermaler
	Nautiker bis Luftverkehrsberufe
	Publizisten bis Bibliothekare, Archivare, Museumsfachleute
	Sozialarbeiter, Sozialpfleger bis Seelsorge-, Kulthelfer
	Vermessungingenieure bis sonstige Ingenieure
	Wirtschafts- und Sozialwissenschaftler, a.n.g., Statistiker bis Naturwissenschaftler a.n.g.
Technicians	Biologischtechnische Sonderfachkraefte bis physikalisch-, mathematisch-technische Sonderfachkraefte
	Chemielaboraten bis Photolaboranten
	Industriemeister, Werkmeister
	Maschinenbautechniker
	Sonstige Techniker
	Techniker des Elektrofaches bis Bautechniker
	Technische Zeichner
	Vermessungstechniker bis uebrige Fertigungstechniker
Crafspeople	Backwarenhersteller bis Konditoren
	Dachdecker
	Elektroinstallateure, -monteure
	Fernmeldemonteure, -handwerker bis Funk-, Tongeraetemechaniker
	Fleischer bis Fischverarbeiter
	Fliesenleger bis Estrich-, Terazzoleger
	Gaertner, Gartenarbeiter bis Waldarbeiter, Waldnutzer
	Kraftfahrzeuginstandsetzer
	Landmaschineninstandsetzer bis Feinmechaniker
	Maurer bis Betonbauer
	Raumausstatter bis sonst. Holz-, Sportgeraetebauer
	Rohrinstallateure
	Schneider bis Textilausruester
	Sonstige Mechaniker bis Uhrmacher
	Stukkateure, Gipser, Verputzer bis Isolierer, Abdichter

Continued on next page

profession	SIAB occupation
	Tischler
	Werkzeugmacher bis Edelmetallschmiede
	Zahntechniker bis Puppenmacher, Modellbauer, Praeperatoren
	Zimmerer bis Geruestbauer
Sales personnel	Bankfachleute bis Bausparkassenfachleute
	Fremdenverkehrsfachleute bis Geldeinnehmer, -auszahler, Kartenverkaeufer, -kontrolleure
	Gross- und Einzelhandelskaufleute, Einkaeufer
	Handelsvertreter, Reisende bis ambulante Haendler
	Krankenversicherungskaufleute (nicht Sozialversicherung) bis Lebens-, Sachversicherungskaufleute
	Speditionskaufleute
	Verkaeufer
	Verlagskaufleute, Buchhaendler bis Tankwarte
Office workers	Buerofachkraefte
	Buerohilfskraefte
	Kalkulatoren, Berechner bis Buchhalter
	Stenographen, Stenotypisten, Maschinenschreiber bis Datentypisten
Production workers	Bauhilfsarbeiter bis sonstige Bauhilfsarbeiter, Bauhelfer, a.n.g
	Bergleute bis Formstein-, Betonhersteller
	Betriebsschlosser, Reparaturschlosser bis Stahlbauschlosser, Eisenschiffbauer
	Blechpresser, -zieher, -stanzer bis sonstige Metallverformer (spanlose Verformung)
	Chemiebetriebswerker
	Chemielaborwerker bis Vulkaniseure
	Dreher
	Eisen-, Metallerzeuger, Schmelzer bis Halbzeugputzer und sonstige Formgiesserberufe
	Elektrogeraete-, Elektroteilemontierer
	Elektrogeraetebauer
	Energiemaschinisten bis Baumaschinenfuehrer
	Feinblechner
	Fraeser bis Bohrer
	Gleisbauer bis sonstige Tiefbauer
	Holzaufbereiter bis Korb-, Flechtwarenmacher
	Keramiker bis Glasbearbeiter, Glasveredler
	Kunststoffverarbeiter
	Landwirte bis Tierpfleger und verwandte Berufe
	Maler, Lackierer (Ausbau)
	Maschinenschlosser
	Maschinenwaerter, Maschinistenhelfer bis Maschineneinrichter o.n.A.
	Metallarbeiter o.n.a.
	Metallpolierer bis Metallkleber und uebrige Metallverbinder

Continued on next page

profession	SIAB occupation
	Metallschleifer bis uebrige spanende Berufe
	Papier-, Zellstoffhersteller bis sonstige Papierverarbeiter
	Pflasterer, Steinsetzer bis Strassenbauer
	Schlosser o.n.a. bis Blech-, Kunststoffschlosser
	Schriftsetzer bis Flach-, Tiefdrucker
	Schweisser, Brennschneider
	Sonstige Montierer
	Spezialdrucker, Siebdrucker bis Druckerhelfer
	Spinner, Spinnvorbereiter bis Fellverarbeiter
	Stahlschmiede bis Rohrnetzbauer, Rohrschlosser
	Warenaufmacher, Versandfertigmacher
	Warenmaler, -lackierer bis Kerammaler, Glasmaler
	Warenpruefer, -sortierer, a.n.g.
	Weinkuefer bis Zucker-, Suesswaren-, Speiseeishersteller
Operators, laborers	Hilfsarbeiter ohne naehere Taetigkeitsangabe
	Kraftfahrzeugfuehrer
	Lagerverwalter, Magaziner
	Posthalter bis Telefonisten
	Schienenfahrzeugfuehrer bis Strassenwarte
	Stauer, Moebelpacker bis Lager-, Transportarbeiter
	Transportgeraetefuehrer
Service personnel	Friseure bis sonstige Koerperpfleger
	Gastwirte, Hoteliers, Gaststaettenkaufleute bis Kellner, Stewards
	Hauswirtschaftsverwalter bis mit Haushaltsscheckverfahren gemeldete Arbeitnehmer
	Kassierer
	Koeche bis Fertiggerichte-, Obst-, Gemuesekonservierer, -zubereiter
	Kuenstlerische und zugeordnete Berufe der Buehnen-, Bild-, Tontechnik bis Artisten, Berufssportler, kuenstlerische Hilfsberufe
	Pfoertner, Hauswarte bis Haus-, Gewerbediener
	Raum-, Hausratreiniger bis Glas-, Gebaeudereiniger
	Soldaten, Grenzschutz-, Polizeibedienstete bis Rechtsvollstrecker
	Strassenreiniger, Abfallbeseitiger bis Maschinen-, Behaelterreiniger und verwandte Berufe
	Uebrige Gaestebetreuer
	Waescher, Plaetter bis Textilreiniger, Faerber und Chemischreiniger
	Werkschutzleute, Detektive bis Waechter, Aufseher
Care personnel	Diaetassistenten, pharmazeutisch-technische Assistenten bis Medizinallaboranten
	Heilpraktiker bis Masseure, Krankengymnasten und verwandte Berufe
	Helfer in der Krankenpflege
	Kindergaertner, Kinderpfleger
	Krankenschwestern, -pfleger, Hebammen

Continued on next page

profession	SIAB occupation
	Sprechstundenhelfer

B Theory

B.1 Proofs and Derivations

B.1.1 Derivation of Equation (4)

We restate (3), explicitly indicating that $I_{k,i,t}$ is a function of potential wages in all K professions:

$$dw_{i,t} = \sum_{k=1}^{K} I_k(w_{1,i,t},, w_{2,i,t}..., w_{k,i,t}, ..., w_{K,i,t})dw_{k,i,t}. \tag{16}$$

To get from marginal to discrete changes, hold constant $w_{l,i,t-1} \forall\ l \geq 2$ first and integrate (16) with respect to the potential wage in profession 1 :

$$w_{i|w_{1,i,t},w_{2,i,t-1},...} - w_{i|w_{1,i,t-1},w_{2,i,t-1},...} = \int_{w_{1,i,t-1}}^{w_{1,i,t}} I_1(w_{1,i,\tau}, w_{2,i,t-1}, ...)dw_{1,i,\tau}.$$

Now, hold constant $w_{l,i,t-1} \forall\ l > k$ at $t-1$ as well as $w_{m,i,t} \forall\ m < k$ at t and integrate with respect to some $w_{k,i,t-1}$. Then, $\forall\ k \in \{1, ..., K\}$:

$$\begin{aligned} & w_{i|w_{1,i,t},...,w_{k,i,t},...,w_{K,i,t-1}} - w_{i|w_{1,i,t},...,w_{k,i,t-1},...,w_{K,i,t-1}} = \\ & = \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})dw_{k,i,\tau}. \end{aligned} \tag{17}$$

Summing all of these elements (17) from $k = 1$ to $k = K$ we get

$$\begin{aligned} & w_{i|w_{1,i,t},...,w_{K,i,t}} - w_{i|w_{1,i,t-1},w_{2,i,t-1},...} = w_{i,t} - w_{i,t-1} = \\ & = \Delta w_{i,t} = \sum_{k=1}^{K} \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})dw_{k,i,\tau}. \end{aligned} \tag{18}$$

The notation of Equation (4) in the main text is therefore somewhat imprecise, as each integral with respect to $w_{k,i,\tau}$ in fact holds constant all the other wages.

B.1.2 Derivation of Equation (6)

First, replace the indicator $I_{k,i,\tau}$ for a specific k in Equation (4) with the linear interpolation (5):

$$\begin{aligned} \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_{k,i,\tau}dw_{k,i,\tau} &= \int_{w_{k,i,t-1}}^{w_{k,i,t}} \left[I_{k,i,t-1} + \frac{I_{k,i,t} - I_{k,i,t-1}}{w_{k,i,t} - w_{k,i,t-1}}(w_{k,i,\tau} - w_{k,i,t-1})\right] dw_{k,i,\tau} \\ &= I_{k,i,t-1}\Delta w_{k,i,t} + \frac{I_{k,i,t} - I_{k,i,t-1}}{w_{k,i,t} - w_{k,i,t-1}} \left[\frac{1}{2}w_{k,i,\tau}^2 - w_{k,i,t-1}w_{k,i,\tau}\right]_{w_{k,i,t-1}}^{w_{k,i,t}} \\ &= I_{k,i,t-1}\Delta w_{k,i,t} + \frac{1}{2}(I_{k,i,t} - I_{k,i,t-1})(w_{k,i,t} - w_{k,i,t-1}) \\ &= \bar{I}_{k,i,t}\Delta w_{k,i,t} \end{aligned}$$

where $\bar{I}_{k,i,t} \equiv \frac{I_{k,i,t}+I_{k,i,t-1}}{2}$ is the worker's "average" profession choice in the two periods. Then, summing up over all k gives Equation (6).

Notice that the approximated variable $I_{k,i,\tau}$ is in fact $I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})$ according to Equation (18). We use $I_{k,i,t-1} = I_k(w_{1,i,t-1}, ..., w_{k,i,t-1}, ..., w_{K,i,t-1})$ and $I_{k,i,t} = I_k(w_{1,i,t}, ..., w_{k,i,t}, ..., w_{K,i}$

in the empirics (and therefore in the linear interpolation) because these are observed in the data. The Monte Carlo simulations in Appendix C1 and in Böhm (2017) indicate that also this approximation is innocuous for identifying the correct task prices.

B.1.3 Sign of Bias for the Baseline Estimation

- Introduce tilde-notation.
- Introduce 2-profession example.

Consider the values entering Equation (9) in each of four cases:

1. if $I_{2,i,t} = I_{2,i,t-1} = 1$, $E(\bar{I}_{2,i,t}\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 1) = E(\tilde{v}_{2,t}|\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} + \Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} > 0, \tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} > 0)$. It is easier to cross the second threshold the larger $\Delta\tilde{\pi}_{2,t}$. That is, $\frac{\partial E(\tilde{v}_{2,t}|I_{2,i,t}=I_{2,i,t-1}=1)}{\partial \Delta\tilde{\pi}_{2,t}} < 0$. If in the base period $\Delta\tilde{\pi}_{2,1} = 0$ but $\Delta\tilde{\pi}_{2,t} > 0$ in some other time t, the estimated conditional expectation from regression (**??**) entering Equation (9) is larger than the true expectation of the error component $E(\bar{I}_{2,i,t}\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 1)$. In order to fit the wage data, this leads to a too small estimate $0 < \widehat{\Delta\tilde{\pi}}_{2,t} < \Delta\tilde{\pi}_{2,t}$ and vice versa if $\Delta\tilde{\pi}_{2,t} < 0$.

2. if $I_{2,i,t} = 1$ and $I_{2,i,t-1} = 0$, $E(\bar{I}_{2,i,t}\tilde{v}_{2,t}|I_{2,i,t} = 1, I_{2,i,t-1} = 0) = \frac{1}{2}E(\tilde{v}_{2,t}|\Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} > -(\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1}) > 0)$. Hence, $\frac{\partial E(\tilde{v}_{2,t}|I_{2,i,t}=1,I_{2,i,t-1}=0)}{\partial \Delta\tilde{\pi}_{2,t}} < 0$ and the same argument as in case 1 applies.

3. if $I_{2,i,t} = 0$ and $I_{2,i,t-1} = 1$, $E(\bar{I}_{2,i,t}\tilde{v}_{2,t}|I_{2,i,t} = 0, I_{2,i,t-1} = 1) = \frac{1}{2}E(\tilde{v}_{2,t}|\Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} < -(\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1}) < 0)$. Hence, $\frac{\partial E(\tilde{v}_{2,t}|I_{2,i,t}=0,I_{2,i,t-1}=1)}{\partial \Delta\tilde{\pi}_{2,t}} < 0$ and again the same argument as in case 1 applies.

4. if $I_{2,i,t} = I_{2,i,t-1} = 0$, $0 \cdot E(\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 0) = 0$ in any case and both the control term entering Equation (9) and the error component that creates the bias are zero.

Given cases 1–4, the estimation unambiguously tends to underestimate rising $\Delta\tilde{\pi}_{2,t}$ (or accelerating relative to $\Delta\tilde{\pi}_{2,1}$) and to overestimate declining $\Delta\tilde{\pi}_{2,t}$ (or decelerating relative to $\Delta\tilde{\pi}_{2,1}$). The baseline estimation model therefore likely provides a lower bound in absolute value to the true changes in relative task prices.

B.1.4 Sign of Bias for Instrumental Variables Estimation

In example (**??**) what remains in the numerator of the bias after instrumenting is Equation (**??**):

$$cov(I_{2,i,t}\tilde{v}_{2,i,t}, I_{2,i,t-1}) = \underbrace{E[I_{2,i,t-1}E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t-1})]}_{(1)} - \underbrace{E(I_{2,i,t}\tilde{v}_{2,i,t})E(I_{2,i,t-1})}_{(2)}.$$

Regarding component (2), we know that $E(I_{2,i,t-1}) \equiv p\,\epsilon(0,1)$ and $E(I_{2,i,t}\tilde{v}_{2,i,t}) > 0$, since $I_{2,i,t}$ positively depends on $\tilde{v}_{2,i,t}$. Therefore, $(2) = pE(I_{2,i,t}\tilde{v}_{2,i,t}) > 0$. Regarding component (1), the outer expectation is $(1-p)\cdot 0 \cdot E(I_{2,i,t}\tilde{v}_{2,i,t}|0) + p \cdot 1 \cdot E(I_{2,i,t}\tilde{v}_{2,i,t}|1) = pE(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t-1} = 1) > 0$, because also conditional on $I_{2,i,t-1} = 1$, $I_{2,i,t}$ positively depends on $\tilde{v}_{2,i,t}$.

The difference

$$(1) - (2) = p[E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t-1} = 1) - E(I_{2,i,t}\tilde{v}_{2,i,t})],$$

however, is likely to be negative because $I_{2,i,t} = \mathbb{1}[\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} + \Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} > 0]$ is likely to vary more with $\tilde{v}_{2,i,t}$ unconditionally than when conditioning on $\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} > 0$.

B.2 Extensions of the Model

B.2.1 Non-Pecuniary Benefits or Forward-Looking Behavior

In the discussion of the main text, individuals are myopic and maximizing only current wages. In this section we show how the model can be reinterpreted in light of forward-looking behavior and non-pecuniary components of the decision to enter different professions.

Generalize Equation (1) to have individuals maximize their utility by choosing the profession that gives the highest

$$U_{k,i,t} = w_{k,i,t} + V_{k,i,a} = \pi_{k,t} + s_{k,i,a} + V_{k,i,a} \,\forall\, k \in \{1, \ldots, K\}, \tag{19}$$

where $w_{k,i,t}$ is the potential wage as in the main text and $V_{k,i,a}$ a non-pecuniary benefit to work in profession k or a continuation value (i.e. expectation of discounted sum of future wages) when choosing this profession in t. As indicated here, $V_{k,i,a}$ can be person- and age-specific (continuation values are likely more important for younger workers) but we will also discuss it to be time-specific (e.g., when the early investment component of work experience becomes more important). It also has to be profession-specific (have a k-index); otherwise this simplifies to the main text where only current wages matter for choices.

Using this generalized Roy model, Equation (6) from the main text becomes

$$\Delta U_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta U_{k,i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta \pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta s_{k,i,a} + \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta V_{k,i,a}, \tag{20}$$

or

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta \pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta s_{k,i,a} + \tilde{V}_{i,a}, \tag{21}$$

where $\Delta U_{i,t} = \Delta w_{i,t} + \Delta V_{i,t}$ and $\tilde{V}_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t}\Delta V_{k,i,a} - \Delta V_{i,t}$ parallels the error term $u_{i,t}$ of Section **??** in which we had idiosyncratic skill shocks. In particular, $\tilde{V}_{i,t}$ is systematically related to sectoral choice, that is, the regressor $\bar{I}_{k,i,t}$. When $I_{k,i,t-1} = I_{k,i,t} \,\forall\, k$ we have $\tilde{V}_{i,t} = 0$ and we expect $\tilde{V}_{i,t} < 0$ when workers move to professions where non-pecuniary benefits or continuation values are higher (vice versa when these are lower). Notice that the non-pecuniary components matter even if they are time- or age-invariant (i.e. $\Delta V_{k,i,a} = 0 \,\forall\, k, i, a$), since $\tilde{V}_{i,t} = -\Delta V_{i,t}$ in Equation (19) implies that wages rise by less if the worker moves to a profession that he values more than his initial profession with regards to other aspects than current wages.

The analogy with $u_{i,t}$ in Section **??** extends to the estimation. If *the change in* the non-pecuniary benefits or continuation values conditional on our control variables does not change over time (i.e. the expectation of $\tilde{V}_{i,t}$ conditional on age, previous and current task choices is time-invariant), our estimation in Equation (8) of the skill-accumulation function $\gamma_{k',k,a}$ in the base period conditionally demeans this error. The estimate of $\gamma_{k',k,a}$ is then a combitiation of the true skill accumulation parameter (and the expectation of the idiosyncratic skill shock) from the main text minus the non-pecuniary gains from changing tasks ($\tilde{V}_{i,t}$ is the inverse of the gain). The estimated task prices however are correct.

One simplified example is with two professions where $k = 2$ carries some homogenous, age- and time-invariant non-pecuniary benefits, i.e. $V_2 > V_1 = 0$ and $\Delta V_1 = \Delta V_2 = 0$. Equation (21) implies that in this case we should see in the data $\Delta w_{i,t} = \bar{I}_{1,i,t}\Delta w_{k,i,1} + \bar{I}_{2,i,t}\Delta w_{k,i,2} - \Delta V_{i,t}$, where $\Delta V_{i,t} = 0$ if the worker doe not change profession, $\Delta V_{i,t} = -V_2$ if he switches from $k = 1$ to $k = 2$ and $\Delta V_{i,t} = V_2$ if he makes the opposite switch. This means that we tend to observe lower wage growth when workers switch to work places with high amenities or continuation values and vice versa when they switch away from them. In the estimation, $\gamma_{k',k,a}$

controls for average wage changes when switching from k' to k, be it for reasons of systematic accumulation, idiosyncratic skill shocks, or these inverse non-wage differentials.

The estimation becomes more difficult if the distribution of $\tilde{V}_{i,t}$ conditional on age, previous and current task choices changes over time. For example, the continuation value of Mgr-Prof-Tech could increase if early career experience in this profession becomes more valuable for life-time earnings due to its rising task prices. We cannot allow for $V_{k,t}$ to flexibly vary over time because this would be perfectly collinear with the task price changes $\Delta\pi_{k,t}$. However, given the concavity of skill accumulation (e.g. Figure **??**) and the different time horizons, it seems clear that a changing continuation value of different professions would affect young workers more than older workers. Therefore, in a robustness check of Section D.1 we split the data into 25-39 and 40-54 year olds and estimate the model on these two samples separately. We find that the results are largely comparable, which makes us confident that potential *changes in* dynamic considerations over time are not sufficiently strong to overturn the qualitative results of the estimation.

B.2.2 Costs of Switching Professions

There may also be pecuniary or non-pecuniary one-off costs of switching professions. We will see that this can be interpreted largely similar to non-pecuniary benefits or continuation values from the previous section.

We can think of two types of switching costs, those that affect wages and those that are non-wage costs. The first type is due to occupation or task-specific skill accumulation and transferability (e.g., Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). Our estimation Equation (8) flexibly allows for this by interpreting $\gamma_{k',k,a}$ to incorporate the wage costs. Relatedly, Cortes (2016, Equation 13; also Cavaglia and Etheridge (2017)), accounts for wage costs of switching using dummy interactions for origin and destination occupations in the wage regression. The other type are pecuniary and non-pecuniary non-wage costs, e.g., financial expenses and psychological stress of moving house to be close to the new job, which are potentially as important as wage costs (e.g., Dix-Carneiro, 2014; Artuç and McLaren, 2015; Cortes and Gallipoli, 2017). We show how the estimation accounts for those costs in the following.

Suppose individuals maximize their utility by choosing the profession that gives the highest

$$U_{k,i,t} = w_{k,i,t} - c_{k',k,a} = \pi_{k,t} + s_{k,i,a} - c_{k',k,a} \; \forall \, k \in \{1, \ldots, K\}, \tag{22}$$

where $c_{k',k,a}$ is a non-wage cost for moving from profession k' to k. In general, this is the expected discounted value of the cost in wage units. We normalize the cost to zero if no switching occurs, i.e. $c_{k',k,a} = 0$ for $k' = k$. Switching costs may be age-specific and they could be individual-specific without any further complications, as in the case of amenities and continuation values above, but we have dropped the i-dependency to save on notation.

Although the utility from different options in (22) is now explicitly dependent on last period's job k' via $c_{k,k'}$, it does not change the Result (20) on $\Delta U_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta U_{k,i,t} = \Delta w_{i,t} - \Delta c_{i,t}$ utility growth from above. This is because we are always comparing just two adjacent periods in the model and in the estimation. In robustness checks (Figure A13) we do vary the period length from one to four and five years in order to check whether our results are sensitive to this. The observed wage growth of individuals in the data (6) becomes

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta\pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta s_{k,i,a} + \tilde{c}_{i,a}, \tag{23}$$

where $\tilde{c}_{i,t} \equiv -\sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta c_{k',k,a} + \Delta c_{i,t}$ and $\Delta c_{i,t} = \sum_{k=1}^{K} \sum_{k'=1}^{K} I_{k,i,t} I_{k',i,t-1} c_{k',k,a}$ is the switching cost. That is, because of $\Delta c_{i,t}$ being positive for them, we tend to observe higher wage growth for workers who make switches. To put it differently, the non-wage cost of switches has to be justified for the worker by its boost to wage income.[28]

In terms of the estimation, again the analogy with $u_{i,t}$ in Section **??** and the previous section holds. The $\gamma_{k',k,a}$ from the skill accumulation function captures the wage effects of potential switching costs, that is, in general it can be a combination of the true skill accumulation parameter, the expectation of the idiosyncratic skill shock, non-pecuniary benefits and continuation value of profession k, and the wage as well as the non-wage switching costs; all of this potentially differing by age. The estimated task prices remain correct.

Finally, there could be large initial wage costs (drops) for some types of profession switches. These drops may then be compensated for by higher subsequent wage growth in the new profession, which workers anticipate basing their switching decision on the longer time horizon. Our baseline estimation (8) allows for such dynamic considerations (see previous section) and the associated wage drop is accounted for by the corresponding $\gamma_{k',k,a}$. Nonetheless, as a robustness check, we estimate the model with four-and five-year periods in addition to one-year periods in order to bypass any initial wage drop using these longer time horizons. This is also helpful to establish robustness *to changes* in initial wage costs (drops) over time, since such changes should have different effects in estimations with short as opposed to long period length if the long-run net gains from switching remain largely unchanged.

B.2.3 Learning About Skills

In the rest of the paper we have assumed that, aside from task prices, all changes in individuals' wages over time are due to systematic skill accumulation and idiosyncratic skill shocks. In this section, we show that the model's interpretation can be widened to include imperfect information about skills and employer learning over time on top of skill accumulation.

Suppose that, as in the learning literature (e.g., Altonji and Pierret, 2001; Gibbons et al., 2005), information about skills is imperfect. Each period an additional noisy signal of the worker's productivity arrives and employers form expectations about skills based on this as well as on all past observable information. Expectations are rational, that is, employers' beliefs are correct on average. Further, information is symmetric, employers are competitive, all market participants are risk neutral, and a spot market for labor exists.

In this setup, workers' potential log wages in each profession equal their expected productivity conditional on all available information:

$$w_{k,i,t} = \pi_{k,t} + E_t(s_{k,i,t}) \; \forall \, k \in \{1, \ldots, K\}, \tag{24}$$

where E_t indicates that we are conditioning on all the information available in t. We assume that workers maximize their log incomes by choosing the profession in which they earn the highest wage. This yields a modified version of Equation (6) for observed wage growth over time:

[28]One simplified example with two professions analogous to the previous section is homogenous, age- and time-invariant switching costs, i.e. $c_{k,k'} = c \; \forall \, k \neq k'$ and $\Delta c_{k,k'} = 0 \; \forall \, k$. Equation (23) implies that in this case we should see in the data $\Delta w_{i,t} = \bar{I}_{1,i,t} \Delta w_{k,i,1} + \bar{I}_{2,i,t} \Delta w_{k,i,2} + \Delta c_{i,t}$, where $\Delta c_{i,t} = 0$ if the worker doe not change profession and $\Delta c_{i,t} = c$ if he does. This means that we tend to observe higher wage growth when workers switch. In the estimation, $\gamma_{k',k,a}$ controls for average wage changes when switching professions.

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta \pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta E_t(s_{k,i,t}), \tag{25}$$

where $\Delta E_t(s_{k,i,t}) \equiv E_t(s_{k,i,t}) - E_{t-1}(s_{k,i,t-1})$ and the linearity in logs allows us to swap sum $\sum$, first difference Δ, and expectations E operators. The skill accumulation (**??**) with idiosyncratic updates of expected skills becomes

$$\Delta E_t(s_{k,i,t}) = \sum_{k'=1}^{K} \sum_{a=1}^{A} I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a] \cdot \gamma_{k',k,a} + v_{k,i,t}, \tag{26}$$

where the first summand is the (expected) average skill accumulation in k of workers aged a previously working in k'. The second summand $v_{k,i,t}$ is an expectation update about individual i's true skill (or its accumulation) in k, which may in general be differentially variable and correlated across professions. The variance of $v_{k,i,t}$ may also decline with age as employers receive more and more precise information about workers' skills (but also the idiosyncratic skill shocks may attenuate with age in the alternative interpretation of the main text).

We have therefore shown that our setup and, by extension, the estimation method remain valid under a basic model of employer learning about skills as an alternative or in addition to systematic skill accumulation and idiosyncratic skill shocks.

B.3 Multiple Fixed Effects as an Alternative Approach

In this section, we examine the multiple fixed effects approach for estimating task prices as an alternative to our proposed method in the main text. We show that under a flexible model of skill accumulation, this approach requires controlling for workers' whole history of profession-specific experience, which is difficult to implement in practice. With idiosyncratic skill shocks, a fundamental endogeneity bias emerges that is due to the fixed effects themselves. The results from the Monte Carlo simulations in Appendix C support our analytical arguments.

Other papers have used fixed effects approaches in order to address worker heterogeneity when estimating task prices (e.g. Cortes, 2016; Cavaglia and Etheridge, 2017).[29] To be specific, consider Cortes' time-varying model for the potential wage of individual i in profession k at time t:

$$w_{k,i,t} = \pi_{k,t} + s_{k,i,t} = \pi_{k,t} + x_{i,t}\gamma_k + \eta_{k,i}. \tag{27}$$

The changing characteristics $x_{i,t}$ can increase skills differently with age or experience in different professions according to γ_k. In addition, $\eta_{k,i}$ are profession-specific time-invariant skill levels, which will be introduced into the regression by individual-profession specific fixed effects. Cortes (2016) and Cavaglia and Etheridge (2017) call these occupation- or sector-*spell* fixed effects, which may lead readers to think mistakenly that workers get a new fixed effect for each new spell when they re-enter a sector they have worked in before. We therefore refrain from using the term spell anywhere in the discussion of the fixed effects approach. If the fixed effect were indeed implemented separately for each individual's new spell in the same sector, only slightly different issues from the ones discussed below would emerge.

[29] In more broadly related settings, Combes et al. (2008) estimate city wage premia, taking into account sorting across locations. Analyzing variation over the business cycle, Solon et al. (1994) account for skill selection into the labor market market, while McLaughlin and Bils (2001) examine skill selection across sectors.

Consistent with (27), Cortes' estimation equation is:[30]

$$w_{i,t} = \sum_{k=1}^{K} I_{k,i,t}\pi_{k,t} + \sum_{k=1}^{K} I_{k,i,t}\eta_{k,i} + \sum_{k=1}^{K} I_{k,i,t}x_{i,t}\gamma_k + u_{i,t}, \tag{28}$$

In the following, we examine whether estimation of Equation (28) may identify the correct task prices. First, consider the case when skill accumulation is only systematic:

$$\Delta s_{k,i,t} = \sum_{k'=1}^{K} I_{k',i,t-1} \cdot \gamma_{k,k'}, \tag{29}$$

where, compared to Equation (**??**) of the main text, we omitted the age-specificity of the accumulation function and the general error term $v_{i,t}$ to save space. Writing this out from when the worker joined the labor market (normalized at experience $x_{i,t} = 0$) gives

$$s_{k,i,t} = \eta_{k,i} + \sum_{k'=1}^{K} [I_{k',i,t-1} + \ldots + I_{k',i,t-x_{i,t}}]\gamma_{k,k'} = \eta_{k,i} + \sum_{k'=1}^{K}\sum_{\tau=1}^{x_{i,t}} I_{k',i,t-\tau}\gamma_{k,k'}, \tag{30}$$

for $x_{i,t} \geq 1$ and $\eta_{k,i}$ the initial skill endowments of i in k at entry into the labor market. Therefore, if we are willing to assume that skill accumulation occurs similarly in each profession of origin ($\gamma_{k,k'} = \gamma_k, \forall k', k$), this simplifies to $s_{k,i,t} = \eta_{k,i} + x_{i,t}\gamma_k$ and Estimation (28) identifies the correct task prices, initial endowments, and skill accumulation parameters. Notice that this specification assumes that labor market experience is not profession-specific, just that general experience is valued differently in different professions.

We have seen in Figure 3 of the main text that wages within in a given profession at a given age strongly depend on workers' previous professions. A model that is more aligned with the evidence therefore allows for experience to be profession-specific, that is, for example allows for the fact that previous managerial experience imparts more managerial skills than previous experience in production jobs. Equation (30) becomes $s_{k,i,t} = \eta_{k,i} + \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'}$, where $x_{k',i,t} \equiv \sum_{\tau=1}^{x_{i,t}} I_{k',i,t-\tau}$ is the worker's profession k' specific experience. Running regression (28) in this case gives an error term $u_{i,t} = \sum_{k=1}^{K} I_{k,i,t}[\sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} - x_{i,t}\gamma_k]$ which varies with $I_{k,i,t}$ and is thus systematically related to the regressors.[31] This yields biased estimates even without any unobserved idiosyncratic skill shocks that lead to endogenous sector switches.

[30] In his estimation, Cortes (2016) uses ten year age bins in $x_{i,t}$, allowing for the convexity of the life-cycle profile similar to our Equation (**??**). However, for demonstration purposes we interpret $x_{i,t}$ as simply the number of years of experience since labor market entry in the discussion that follows. Other ancillary control variables in Cortes' as well as Cavaglia and Etheridge's empirical models are omitted for brevity.

[31] For example, somewhat imprecisely, if skill accumulation for abstract managerial, professional, and technical professions (MPT) *within* MPT is faster than on average across all professions (i.e. $\gamma_{k,k} > \gamma_k$ if $k = MPT$), then $E\left(u_{i,t}|I_{MPT,i,t-1} = 1, I_{MPT,i,t} = 1\right) > E\left(u_{i,t}|I_{MPT,i,t} = 1\right)$. But when the (relative) task price of MPT rises over time, $\pi_{MPT,t} > \pi_{MPT,t-1} > \pi_{MPT,t-2}$, then, conditional on the fixed effects and other controls, the probability of having chosen MPT last period already rises over time and thus the "unconditional" expectation of the error term for those who choose MPT this period increases (i.e. $E\left(u_{i,t}|I_{MPT,i,t} = 1\right) > E\left(u_{i,t}|I_{MPT,i,t-1} = 1\right)$). That is, in this example, when $\pi_{MPT,t}$ are large in Equation (28) and a worker chooses $I_{MPT,i,t} = 1$, also his $u_{i,t}$ is expected to be large and we overestimate the MPT task price (and vice versa when $\pi_{MPT,t}$ is small). We therefore overestimate changes in MPT task prices here. In general, however, it is difficult to sign the bias in these specifications.

The correct fixed effects regression for task prices is instead

$$w_{i,t} = \sum_{k=1}^{K} I_{k,i,t}\pi_{k,t} + \sum_{k=1}^{K} I_{k,i,t}\eta_{k,i} + \sum_{k=1}^{K} I_{k,i,t} \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + u_{i,t}, \tag{31}$$

that is, it controls for all previous profession-specific experience separately. While this is conceptually possible to do, its practical implementation is difficult. It introduces many parameters to be estimated (even more when we realistically allow for profession-specific skill accumulation to vary with age; e.g., see general skill accumulation Equation (**??**) and evidence in Figure **??**) and it requires high-quality panel data in order to compute the full profession- and age-specific work experience history of each individual.

Cortes (2016) and Cavaglia and Etheridge (2017) account for the fact that labor market experience is profession-specific by introducing controls for occupation- and job-specific tenure, respectively, into regression Equation (28).[32] However, in order to deal with the growth in the number of parameters and the length of the employment history information that is required, both papers assume that tenure only affects the current job and that workers lose all of its effect once they switch. Among others, this rules out the differential effects of profession-specific experience in other professions that were documented in Figure 3. It underscores that a first-differenced regression such as our Equation (8) is in important respects more capable of modeling rich and realistic skill accumulation, and thereby identifying the correct task prices, than the fixed effects approach.

Finally, notice that the identification of all parameters in the fixed effects approach also requires a base period. This is because one period is needed to absorb the individual fixed effects and a second period to identify the γ skill accumulation coefficients if they are allowed to flexibly vary with profession and age.[33] Only in a third period can then the task prices $\pi_{k,t}$ be separately identified. This is, maybe unsurprisingly, the same as in our proposed estimation method (8), where we take the initial change between $t = 0$ and $t = 1$ as the base period.

The key difference between our new method proposed in the main text and the fixed effects approach however arises in the presence of idiosyncratic skill shocks, which were strongly suggested by the evidence of Section 2.3. With idiosyncratic skill shocks, the right-hand-side of Equation (30) becomes:

$$s_{k,i,t} = \eta_{k,i} + \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}. \tag{32}$$

The regression error in Equation (31), $u_{i,t} \equiv \sum_{k=1}^{K} I_{k,i,t} \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}$, now systematically depends on the full history of previous idiosyncratic skill shocks, which influence current choices (i.e. the regressors in Equation (31)). Therefore, we get a classical endogeneity bias. One might expect that the sector-experience-specific controls in regression (31) largely address this problem, similar to our differenced approach (8). But this is not the case.

[32] Of course, there may also be proper tenure effects whereby wage growth, in addition to profession-specific experience, depends on the exact tenure in the current job. Given the rich SIAB panel data, it would be relatively straightforward to extend our skill accumulation Equation (**??**) and include this in the estimation.

[33] Instead, one could make a functional form assumption; for example on the age profile of the γ, assuming that it is linear. Then, in a three-period setting, $\eta_{i,k}$ would be identified in the initial period, the γs as the average wage growth between periods $t = 1$ and $t = 2$, and the $\pi_{k,2}$s relative to the $\pi_{k,1}$s as the deviation of wages in $t = 2$ from what is predicted by $\eta_{i,k}$ and the γs. Therefore, the $\pi_{k,2}$ estimates in this case would be entirely due to the linear-in-age functional form assumption on γ.

To see the argument and the bias most clearly, suppose for simplicity that all time-varying skill parameters, which are themselves demanding to model in the fixed effects approach as we discussed, are zero ($\gamma_{k,k'} = 0$). Suppose also that there are only two sectors and consider first the base period where we assume that $\pi_{k,1} = \pi_{k,0} = 0$ for $k\epsilon\{1,2\}$. In this case, simplified wage Equation (31) becomes

$$w_{i,t} = \eta_{1,i} + I_{2,i,t}\tilde{\eta}_{2,i} + v_{1,i,t} + I_{2,i,t}\tilde{v}_{2,i,t} \text{ for } t\epsilon\{0,1\}, \quad (33)$$

where $\tilde{\eta}_{2,i} \equiv \eta_{2,i} - \eta_{1,i}$ and $\tilde{v}_{2,i,t} \equiv v_{2,i,t} - v_{1,i,t}$ are relative skill endowments and skill shocks parallel to the notation in the main text. The regression (33) is classically endogeneity-biased because the error term $I_{2,i,t}\tilde{v}_{2,i,t}$ most likely positively correlates with the regressor $I_{2,i,t}\tilde{\eta}_{2,i}$. This will lead to an overestimation of $\tilde{\eta}_{2,i}$, for example.

If, in order to account for this correlation along the lines of the main text, we introduce choice specific controls, estimation Equation (33) becomes

$$w_{i,t} = \eta_{1,i} + I_{2,i,t}\tilde{\eta}_{2,i} + E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1}) + error_{i,t},$$

with $error_{i,t} \equiv v_{1,i,t} + [I_{2,i,t}\tilde{v}_{2,i,t} - E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1})]$. Since we identify from the wage growth of sector stayers (for a switcher the fixed effects together with choice specific controls are not identified), consider $E(\tilde{v}_{2,i,t}|I_{2,i,t} = I_{2,i,t-1} = 1, \tilde{\eta}_{2,i}) = E(\tilde{v}_{2,i,t}|\tilde{\eta}_{2,i} > 0, \tilde{\eta}_{2,i} + \tilde{v}_{2,i,t} > 0)$ for profession $k = 2$. So even if the correct average $E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1})$ (not conditioned on $\tilde{\eta}_{2,i}$) were identified, the error term in this regression varies systematically with the fixed effect in the regressor (in particular, most likely $\frac{\partial E(\tilde{v}_{2,i,t}|\tilde{\eta}_{2,i}>0, \tilde{\eta}_{2,i}+\tilde{v}_{2,i,t}>0)}{\partial \tilde{\eta}_{2,i}} < 0$). Therefore, $\tilde{\eta}_{2,i}$ identified from profession 2 stayers should be downward-biased and, of course, also the $\gamma_{k,k'}$ are not correctly estimated in the first place. With these biases already from the base period, not only will also the task price estimates in the main sample period $\pi_{k,t}, t > 1$ be potentially severely biased but also will it be hard to sign the direction of these biases. This is a reflection of the fact that fixed effects estimations fundamentally require the exogenous mobility assumption. Relying in the estimation on the wage growth of stayers in a profession does not help to alleviate any resulting biases.

C Monte Carlo Evidence

In this section we provide Monte Carlo evidence for the performance of the estimation method proposed in this paper under various assumptions about the data generating process, including skill accumulation, the distribution of skill shocks, price trends in the base period, and costs of switching.

We construct panel datasets similar in structure to the SIAB and apply our estimation method to those datasets to back out prices previously fed in to construct workers' careers over their life cycle. To resemble basic moments of the SIAB, we randomly draw initial observations of 5,000 individuals from the SIAB, including their initial wages, occupational choices, age (25 - 54) and year (1975 - 2010) of first observation. We then merge prices and skill accumulation parameters previously estimated for the main SIAB sample (see Figure **??**) to that sample and construct the initial skill of an individual as the difference between the initial wage and the estimated price of the profession the worker is initially observed in:

$$s_{k,i,t_{i,0}} = w_{i,t_{i,0}} - \pi_{k,t_{i,0}} \quad \text{if} \quad i \in k \tag{34}$$

where $t_{i,0} \in \{1975, \dots, 2010\}$ is the year a worker is first observed. As the initial choice must also be optimal $w_{k,i,t_{i,0}} \geq w_{k',i,t_{i,0}} \forall k'$, we have a natural bound for the skills a worker possesses in the remaining sectors k' given by:

$$s_{k',i,t_{i,0}} \leq s_{k,i,t_{i,0}} + \pi_{k,t_{i,0}} - \pi_{k',t_{i,0}} \quad \text{if} \quad i \in k \tag{35}$$

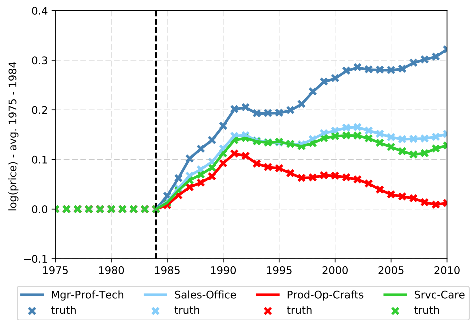
We draw the initial skills separately and independently for every worker in the sample from a truncated normal distribution with the upper bound given by $s_{k,i,t_{i,0}} + \pi_{k,t_{i,0}} - \pi_{k',t_{i,0}}$. We set the location parameter $\mu_{k,i,t_{i,0}} = s_{k,i,t_{i,0}} + \pi_{k,t_{i,0}}$ and fix the scaling parameter $\sigma = 3$ across workers[34]. For the following years of a worker's life cycle, we then simulate workers' wage growth as the sum of systematic skill growth and price growth. On top of that, we add skill shocks randomly depending on the specification and finally let workers choose their preferred sector based on comparative advantage (possibly including costs of switching) according to Equation (2). We repeat this until a worker's maximal age of 54 is reached or the sample period ends. We repeat this exercise for 50 Monte Carlo repetitions and estimate price and skill changes on each sample. We then compute the average price trends and skill accumulation function across repetitions.

Figure A1 shows the results for a Monte Carlo exercise where wage growth could only stem from price growth or systematic skill growth but not from idiosyncratic shocks.

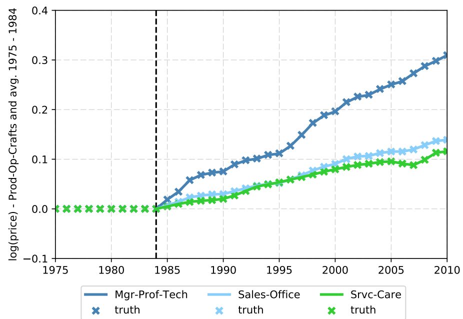
[34]Note that the method removes all time constant variables by first differencing and so is robust to any choice of initial skills and their correlations with each other. We employed the truncated normal distribution for computational reasons only.

Figure A1: Baseline

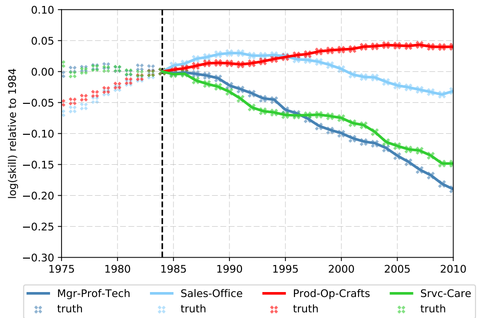
(a) Cumulative prices



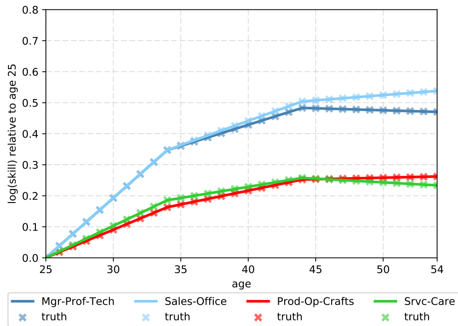
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



(d) Skill Accumulation of Stayers



Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Clearly, the proposed method is able to estimate skill accumulation and task price trends from observed wage changes when skill changes are only systematic and the function describing those changes is time invariant. The approximation in Equation (5) turns out irrelevant for the estimates (we have checked this in various modifications). The next four subsections discuss further possible challenges to our approach, evaluate the resulting biases, and discuss their empirical relevance.

C.1 Idiosyncratic Shocks

Making the idiosyncratic error $u_{k,i,t}$, sector-specific, as in Equation (7), introduces an endogeneity bias which attenuates our estimates, and this bias is rising with the standard deviation of the error. This subsection shows that the bias lies within tight bounds under empirically realistic assumptions on the errors' dispersions.

Figure A2 depicts the results when the errors are drawn from a Gumbel (Extreme Value Type I) distribution with parameters μ, β set so that the errors' standard deviation $\sigma_u = \frac{\pi}{\sqrt{6}}\beta$ is equal to the standard deviation of log wage growth across year in the SIAB data and the mean $\mu + \beta\gamma$ is equal to zero.[35] Note that the standard deviation of wage growth is a complicated

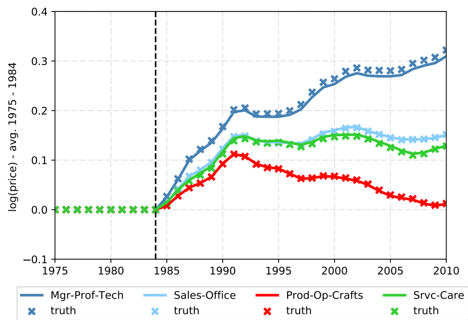
[35] γ is the Euler-Mascheroni constant ≈ 0.57721.

product but likely an upper bound for the standard deviation of skill shocks, which our Monte Carlo analyses confirm. This is because the standard deviation of wage growth is not only a function of the dispersion of skill shocks but also of wage growth due to switching, systematic skill growth and changes in prices.

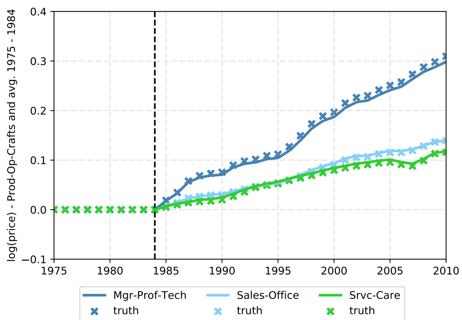
The results indicate that indeed there is a moderate downward bias for the relative prices as shown theoretically in Appendix B.1.3. Compared to the assumed trend in prices, the bias seems to be negligible in empirical applications though.

Figure A2: $u_{i,t,k} \sim$ Gumbel s.t. $\sigma_u = \sigma^{\text{SIAB}}_{\Delta\log(w_{i,t})}$

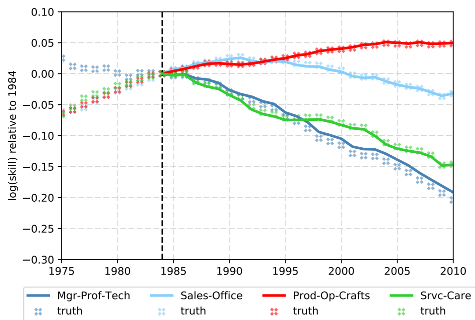
(a) Cumulative prices



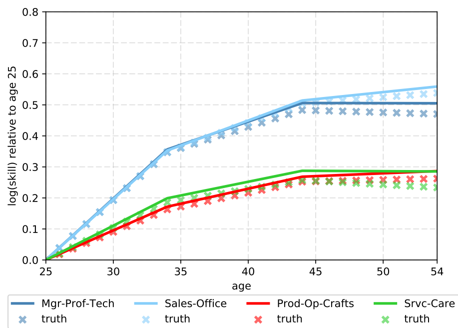
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



(d) Skill Accumulation of Stayers



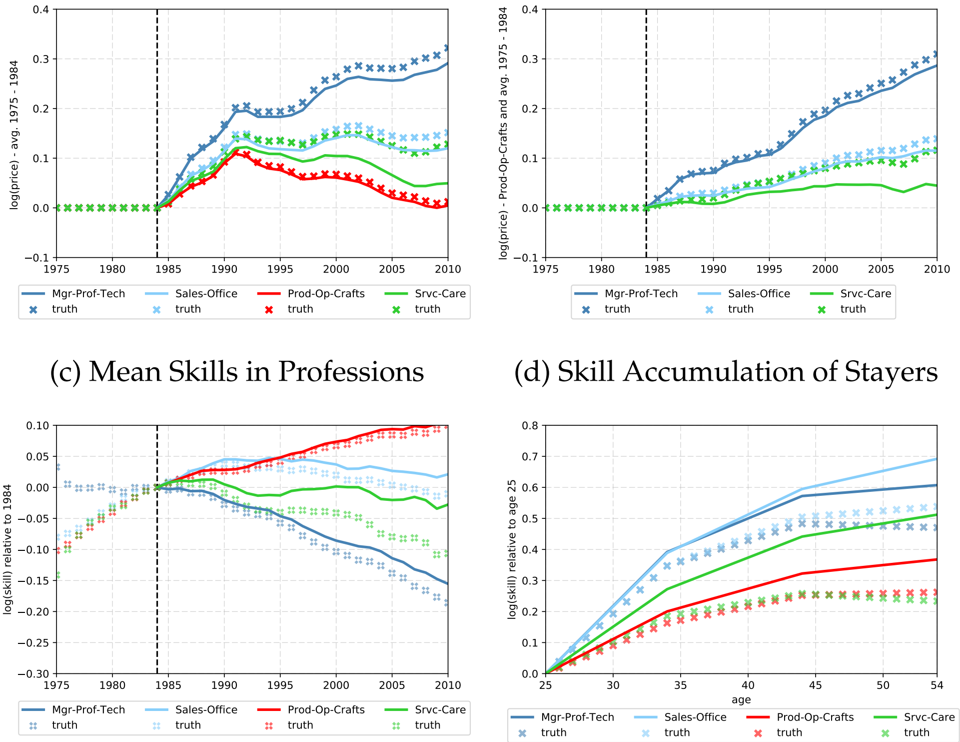
Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

In the next Figure A3, we increase the standard deviation of $u_{k,i,t}$ to two times the standard deviation of log wage growth observed in the SIAB data so that the dispersion of log wage growth in the Monte Carlo samples approximately doubles as well. Clearly, the downward bias for the relative price estimates increases but is still moderate. So overall, we consider the endogeneity problem due to sector specific skill shocks to be of limited importance in empirical applications of our method.

Figure A3: $u_{i,t,k} \sim$ Gumbel s.t. $\sigma_u = 2 \cdot \sigma^{\text{SIAB}}_{\Delta \log(w_{i,t})}$

(a) Cumulative prices (b) Relative to Prod-Op-Crafts

(c) Mean Skills in Professions (d) Skill Accumulation of Stayers



Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

C.2 Switching Costs

Appendix section B.2.2 derived the non importance of switching costs for our approach already. Here, we demonstrate this result using simulated data. For that, we assume that every worker has to pay a monetary cost when wanting to switch, which is individual specific and equal to $c = 0.01 \cdot w_{i,t}$.[36] This cost therefore reduces the number of switchers. To see whether switching costs bias our results we therefore make prices diverge more strongly, leading to more switching because of price changes.

Figure A4 panel (a) depicts how employment shares evolved over time in the SIAB data. Panel (b) plots the same with simulated data where no switching costs were introduced. The changes in employment in the Monte Carlo datasets are very similar. Panel (c) shows the results after introducing switching costs makes fewer workers switch, especially out of Prod-Op-Crafts. Panel (d) then plots employment shares with the same switching costs but price trends which diverge more strongly.

Clearly, choosing $c = 0.01 \cdot w_{i,t}$ in combination with stronger price trends leads to similar changes in the employment distribution, i.e. panels (b) and (d) are similar. The question we ask

[36] The results are robust to setting the costs equal for every worker or only equal for every worker within a sector.

now is: can we still back out the price trends (which are assumed to be stronger than before) even with switching costs?

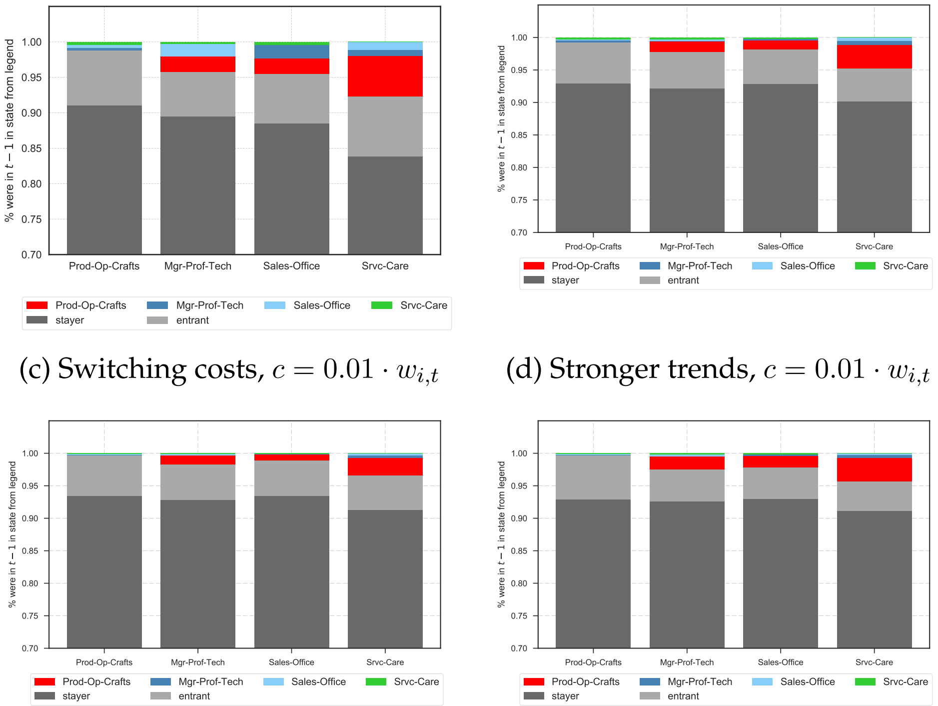
Figure A4: Switching Patterns with Fixed Costs

(a) SIAB

(b) Monte Carlo

(c) Switching costs, $c = 0.01 \cdot w_{i,t}$

(d) Stronger trends, $c = 0.01 \cdot w_{i,t}$



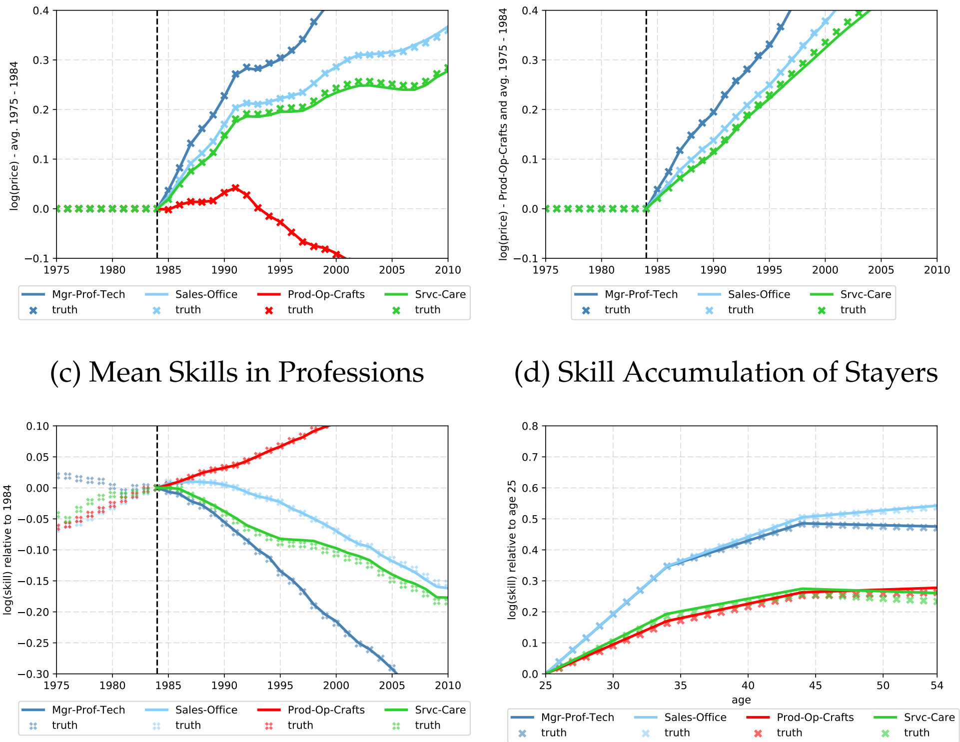
Source: SIAB data and simulated data, own calculations. The bars show the fraction of switchers into sectors. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

The answer to this question is given by Figure A5 showing that the introduction of switching costs does not bias our results.

Figure A5: Switching Costs, Stronger Price Trends

(a) Cumulative prices (b) Relative to Prod-Op-Crafts

(c) Mean Skills in Professions (d) Skill Accumulation of Stayers



Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

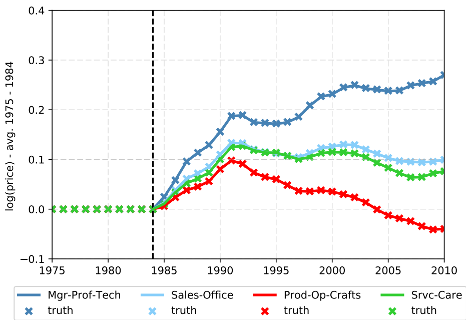
C.3 Trends in Base Period

The interpretation of the estimated price changes depends on price changes in the base period, which we use to estimate systematic skill accumulation over the life cycle as discussed in section 3.2. Here we show that even if that identifying assumption is not fulfilled, we still estimate an important parameter namely price changes relative to the mean price change of a certain sector within the base period 1975 - 1984, i.e. the acceleration or deceleration of price changes.

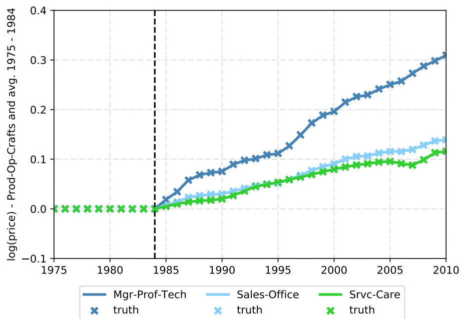
Figure A6 plots the results when trends are equal in the base period which is no problem at all for estimated relative task prices.

Figure A6: Same trends in Base Period

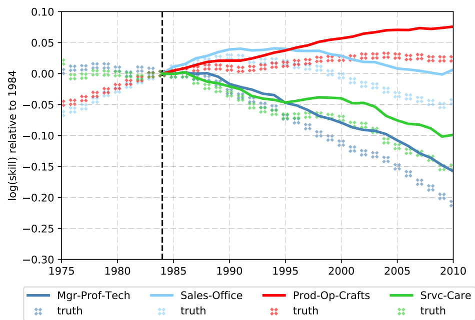
(a) Cumulative prices



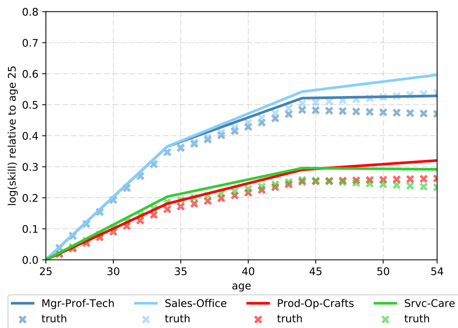
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



(d) Skill Accumulation of Stayers

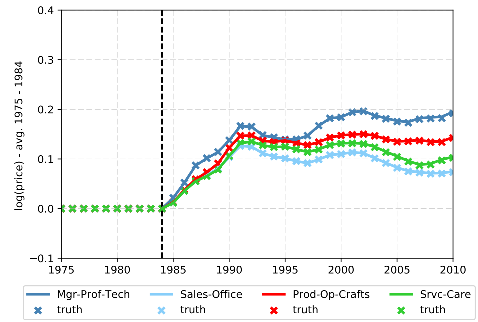


Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

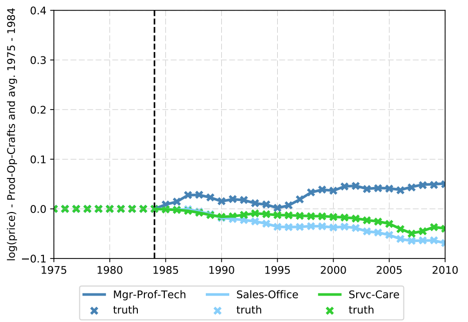
Figure A7 plots the results when trends are not equal in the base period. Then the interpretation of the results changes. Clearly, the interpretation of the results changes as we always subtract the true mean price change in the base period ($\neq 0$ with trends in the base period) from the price changes after the base period. However, we estimate those a- or decelerations without bias.

Figure A7: Different trends in Base Period

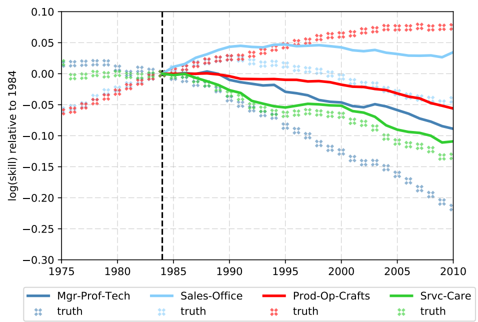
(a) Cumulative prices



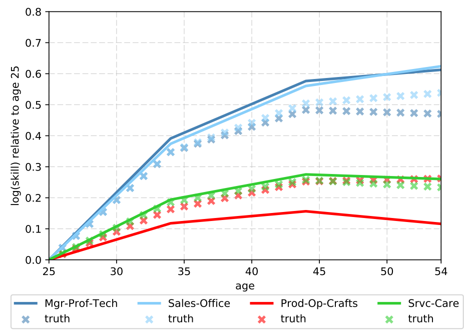
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



(d) Skill Accumulation of Stayers



Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

C.4 Comparison with a Fixed Effects Approach

1. Cortes and our method are equivalent if workers only accumulate skills in k for k but not for another k'.

2. If that is the case, however, Cortes has a bias.

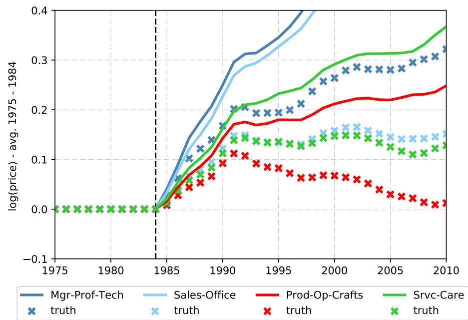
3. Need to check how badly Cortes does with skill shocks.

This section shows that a related approach using multiple fixed effects is only equivalent to our approach when there is no systematic skill accumulation but fails to include systematic skill accumulation over the life cycle. It completely breaks down when on top of systematic skill accumulation there are idiosyncratic shocks which violate the exogenous mobility assumption as described in section B.2.2.

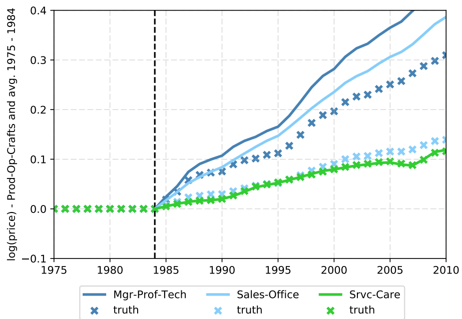
Figure A8 shows the results when there is only systematic skill accumulation. Clearly, the results obtained with an approach as described in Equation (31) are biased.

Figure A8: Multiple Fixed Effects, no shocks

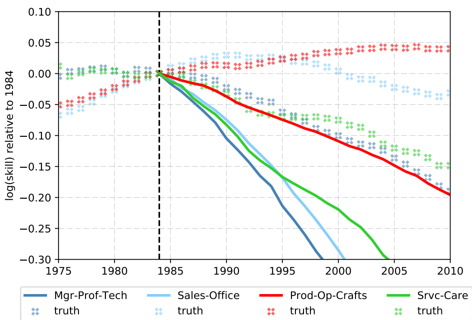
(a) Cumulative prices



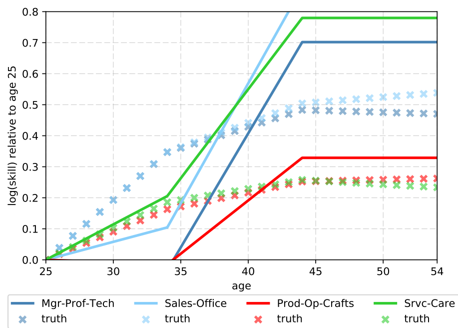
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



(d) Skill Accumulation of Stayers

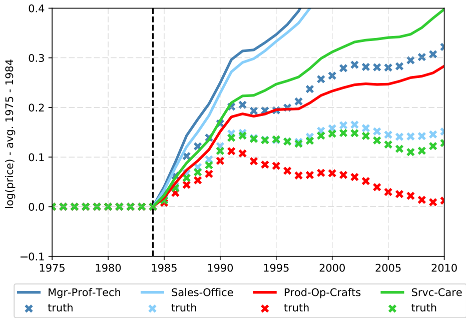


Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

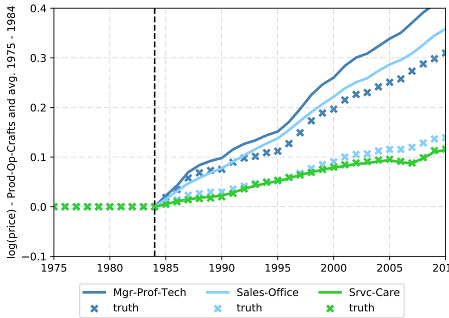
Figure A9 shows the results when there is systematic skill accumulation and skill shocks on top of this, making the fixed effects method fail completely.

Figure A9: Multiple Fixed Effects, $u_{i,t,k} \sim \text{Gumbel s.t. } \sigma_u = \cdot\sigma^{\text{SIAB}}_{\Delta\log(w_{i,t})}$

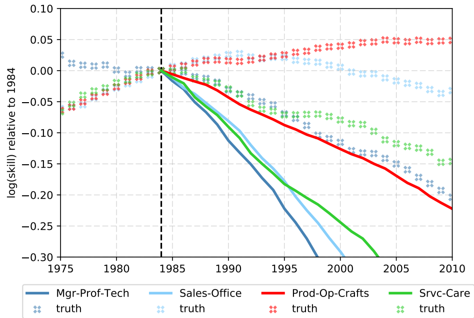
(a) Cumulative prices



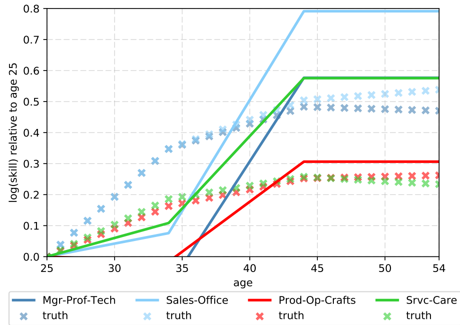
(b) Relative to Prod-Op-Crafts



(c) Mean Skills in Professions



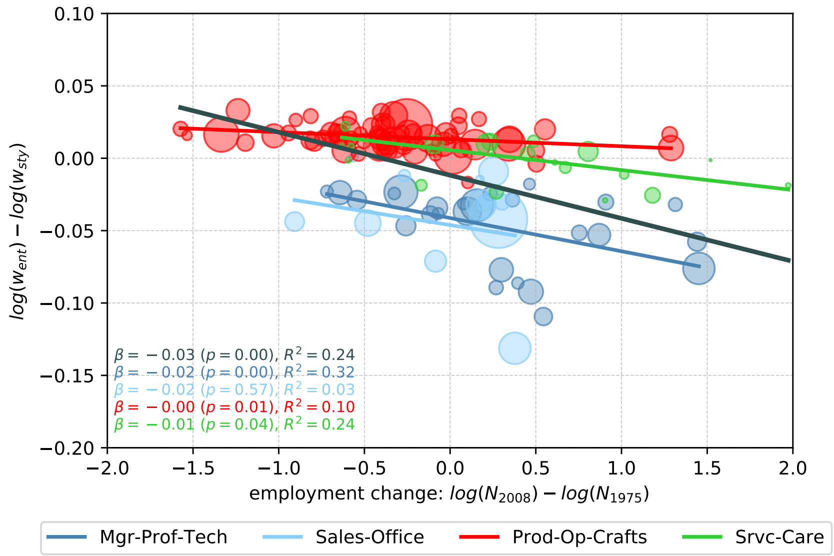
(d) Skill Accumulation of Stayers



Source: SIAB data and simulated data, own calculations. The solid lines in the upper two panels show the estimated price changes in accumulated form relative to the average price changes between 1975 and 1984 - absolute and relative to Prod-Op-Crafts. The crosses mark the true parameters with which the datasets were constructed. The lower left panel shows average skills within sectors relative to the average change between 1975 and 1984. The lower right panel plots the estimated skill accumulation of stayers. Monte Carlo size: 5,000 individuals, 50 replications.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

D Further Empirical Results

Figure A10: Residual wages of entrants minus wages of stayers



Source: SIAB data, own calculations. One bubble in the graphs represents one of the 120 occupations in the SIAB data. The size of one bubble is proportional to the number of workers within one occupation. The vertical position was computed by subtracting the average log wage of occupational stayers from the average wage of entrants. TResidual wages were obtained from a regression of log wages on age, age squared, experience within an occupation in years and its square, dummies for industry as well as worker times occupation fixed effects. The horizontal position was calculated by subtracting log employment in 1975 from log employment in 2010. The regression line in dark gray was fitted weighting each occupation by its size. The colored lines were fitted within the respective four professions. P-values are in parentheses.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Table A2: Mean task measures by profession

	analytical	interactive	routine	manual
Mgr-Prof-Tech	0.37	0.39	0.20	0.14
Sales-Office	0.19	0.34	0.13	0.10
Prod-Op-Crafts	0.09	0.16	0.32	0.26
Srvc-Care	0.23	0.30	0.20	0.29

Source: Qualifications and Career Surveys, own calculations. In the QCS surveys, workers are asked what tasks they perform in their job, e.g. "how often do you repair stuff". They provide answers on a scale: "never, sometimes, often". I assign numerical values $\{0, 0.3, 1\}$ to these categories, respectively. We group all the questions into the four categories mentioned in the table and average over professions implying that the four task categories do not need to sum up to one as some professions might be more intense in overall tasks than others. The six different QCS waves were pooled together as the questions are hardly comparable between waves. For more details see, for instance, Spitz-Oener (2006).
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Table A3: Labor Market Entrants' Profession Choices

(a) Employment by Cohort

	[1950, 1960)	[1960, 1970)	[1970, 1980)	[1980, 1985)
Mgr-Prof-Tech	0.12	0.10	0.12	0.18
Sales-Office	0.18	0.15	0.18	0.20
Prod-Op-Crafts	0.65	0.70	0.62	0.54
Srvc-Care	0.05	0.06	0.08	0.08

Source: SIAB data, own calculations. The numbers show the fraction of workers who start within a certain profession and were born in the respective cohorts conditional on not being unemployed or out of the labor force and conditional on starting the career at age 30 or younger.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

D.1 Robustness Checks

Section 4 of the main text has estimated the skill accumulation functions and changes in task prices for different professions. We found that task prices in fact polarized in Germany during 1985–2010, contrary to changes in average wages across professions. This section shows that these results are robust to various alternative sample definitions and estimation specifications. We start by providing evidence regarding the identification assumption of time-invariant skill accumulation.

D.1.1 Constancy of Skill Accumulation

Section 3.2 showed that, if skill accumulation in professions is time-invariant, we can consistently estimate it in the base period and control for it thereafter. Since we interpret general accelerations or decelerations in wage growth *between* professions as changes in task prices, this constancy of skill accumulation assumption mainly implies that the relative $\gamma_{k',k,}$ *within* professions do not change over time.

Table 1 summarizes evidence in this respect, reporting 95% confidence intervals of individual wage growth within professions in the base period of 1976–1984, in 1985–1995, and during 1996–2010. We compute the yearly wage growth for the same age

Table A4: Wages of Marginal Workers relative to Stayers' Wages

	$\log(w_{\text{ent}})$	$\log(w_{\text{lvr}})$	$\log(w_{\text{ent} \mid \text{lvr}})$	P(ent) − P(lvr)
Mgr-Prof-Tech	-0.122	-0.075	-0.099	0.007
Sales-Office	-0.102	-0.077	-0.090	0.004
Prod-Op-Crafts	-0.031	-0.088	-0.060	-0.006
Srvc-Care	-0.076	-0.104	-0.089	0.011

Source: SIAB data, own calculations. Columns two, three and four show residual wages of profession entrants, leavers as well as entrants or leavers, respectively, minus the residual wages of profession stayers pooled over years after 1984. The residuals were obtained from a regression of log wages on age, age squared, education dummies, industry dummies, sector specific experience, experience squared, detailed 120 occupation dummies and year dummies. The last column indicates the share of entrants minus leavers which is negative if a sector shrinks and positive vice versa.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

Table A5: Percentages of Switchers and Stayers Across Categories from ($t-1$ to t)

t t - 1	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	16.85	0.25	0.15	0.04
Sales-Office	0.29	13.00	0.18	0.04
Prod-Op-Crafts	0.34	0.26	47.74	0.23
Srvc-Care	0.04	0.05	0.19	4.59
unem	0.20	0.18	1.03	0.16
olf	0.50	0.31	0.68	0.20

Table A6: Percentages of Switchers from ($t-1$ to t), by Origin

t t - 1	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	94.92	1.43	0.86	0.21
Sales-Office	2.08	93.15	1.30	0.30
Prod-Op-Crafts	0.67	0.51	94.38	0.46
Srvc-Care	0.86	0.97	3.62	88.00
unem	3.60	3.29	18.56	2.98
olf	7.13	4.46	9.73	2.83

Table A7: Wages of Switchers from ($t-1$ to t), Before Switching

t t - 1	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care	unem	olf
Mgr-Prof-Tech	57346	51372	37956	35987	43722	42138
Sales-Office	50653	46082	29865	28491	33949	31969
Prod-Op-Crafts	38702	31671	34069	26648	26545	25676
Srvc-Care	34874	28919	24555	32095	22632	21320

groups as in the price estimations separately and then deduct the mean wage growth of old workers (45 to 54 year olds) from the wage growth of younger workers (25 to 34 or 35 to 44 year olds). In the model, all workers should face the same task prices within a profession independent of their age. Therefore, normalizing wage growth of old workers with that of young workers should eliminate the change in prices from the change in wages, giving us the change in relative skills.

The positive coefficients in Table 1 show once again that wage growth at older ages

Table A8: Percentages of Switchers from ($t-1$ to t), by Destination

t t - 1	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	92.50	1.81	0.31	0.72
Sales-Office	1.59	92.49	0.36	0.81
Prod-Op-Crafts	1.85	1.84	95.55	4.38
Srvc-Care	0.25	0.36	0.38	87.23
unem	1.09	1.29	2.05	3.13
olf	2.72	2.21	1.36	3.74

Table A9: Wages of Switchers from ($t-1$ to t), After Switching

t t - 1	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	58717	53131	38273	36492
Sales-Office	53170	47209	30585	28741
Prod-Op-Crafts	40650	32506	34406	26532
Srvc-Care	36983	30388	25805	32485
unem	39134	30397	25193	22197
olf	42022	33167	24946	22618

Table A10: Percentages of Switchers and Stayers Across Categories from ($t-2$ to t)

t t - 2	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	16.25	0.44	0.25	0.06
Sales-Office	0.51	12.49	0.29	0.07
Prod-Op-Crafts	0.63	0.45	46.71	0.39
Srvc-Care	0.08	0.08	0.29	4.21
unem	0.28	0.25	1.31	0.22
olf	0.86	0.49	0.94	0.29

Table A11: Percentages of Switchers from ($t-2$ to t), by Origin

t t - 2	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	91.94	2.49	1.43	0.34
Sales-Office	3.63	89.18	2.11	0.49
Prod-Op-Crafts	1.23	0.88	91.49	0.76
Srvc-Care	1.47	1.65	5.70	81.84
unem	5.21	4.61	24.62	4.22
olf	12.65	7.25	13.85	4.25

is slower than when 25–34 years old and that this is more strongly so for Mgr-Prof-Tech and Sales-Office professions. These differences have also largely stayed constant for Prod-Op-Crafts and Srvc-Care over time, suggesting wage growth over the life cycle in the two lower-earning professions is similar to 35 years ago and consistent with a time-invariant skill accumulation function.

Table A12: Wages of Switchers from ($t-2$ to t), Before Switching

t t - 2	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care	unem	olf
Mgr-Prof-Tech	57344	51763	38402	36853	44551	44561
Sales-Office	50688	46069	30228	29616	34891	33730
Prod-Op-Crafts	38500	32074	34197	27619	27333	26416
Srvc-Care	34582	29301	24919	32686	23176	22111

Table A13: Percentages of Switchers from ($t-2$ to t), by Destination

t t - 2	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	87.37	3.10	0.51	1.16
Sales-Office	2.74	87.93	0.59	1.30
Prod-Op-Crafts	3.38	3.17	93.79	7.40
Srvc-Care	0.41	0.60	0.59	80.35
unem	1.49	1.73	2.63	4.29
olf	4.62	3.47	1.89	5.50

Table A14: Wages of Switchers from ($t-2$ to t), After Switching

t t - 2	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	60155	55110	38861	37844
Sales-Office	55494	48339	31307	29893
Prod-Op-Crafts	42089	33595	34874	27298
Srvc-Care	38725	32110	27001	33484
unem	38832	30737	25568	22536
olf	43513	35037	25873	24022

Table A15: Percentages of Switchers and Stayers Across Categories from ($t-5$ to t)

t t - 5	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	15.12	0.83	0.45	0.11
Sales-Office	0.97	11.60	0.52	0.12
Prod-Op-Crafts	1.43	0.90	45.02	0.75
Srvc-Care	0.14	0.15	0.46	3.59
unem	0.36	0.31	1.54	0.27
olf	1.43	0.75	1.17	0.37

In contrast, the differences in wage growth between age groups in Mgr-Prof-Tech and Sales-Office have somewhat widened (i.e., become larger). This suggests that skill accumulation in these professions may have steepened over time, which could impact our task price estimates. In robustness checks below, we therefore split the sample into "younger" workers aged 25–39 and "older" workers aged 40–54 and re-estimate the model for these groups separately. Consistent with the results in Table 1, the estimated relative task prices for Mgr-Prof-Tech and Sales-Office professions in the younger

Table A16: Percentages of Switchers from ($t-5$ to t), by Origin

t t - 5	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	86.80	4.79	2.59	0.62
Sales-Office	6.89	82.25	3.65	0.87
Prod-Op-Crafts	2.75	1.73	86.23	1.44
Srvc-Care	2.88	2.98	9.33	72.33
unem	7.04	6.05	29.70	5.31
olf	23.32	12.27	19.14	5.99

Table A17: Wages of Switchers from ($t-5$ to t), Before Switching

t t - 5	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care	unem	olf
Mgr-Prof-Tech	56329	51515	39449	38079	45696	47979
Sales-Office	50239	45233	31207	31350	36454	36938
Prod-Op-Crafts	38060	32891	34153	29225	28816	28520
Srvc-Care	34517	30184	26116	33334	24209	23849

Table A18: Percentages of Switchers from ($t-5$ to t), by Destination

t t - 5	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	77.71	5.74	0.92	2.05
Sales-Office	4.99	79.72	1.05	2.36
Prod-Op-Crafts	7.37	6.21	91.58	14.44
Srvc-Care	0.73	1.02	0.94	68.85
unem	1.87	2.16	3.13	5.27
olf	7.33	5.16	2.38	7.02

Table A19: Wages of Switchers from ($t-5$ to t), After Switching

t t - 5	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Mgr-Prof-Tech	63760	59002	40596	40250
Sales-Office	60262	50830	32814	31741
Prod-Op-Crafts	45057	36183	35764	28890
Srvc-Care	42549	35686	29009	35299
unem	42315	33410	27103	23937
olf	49809	40956	28145	27399

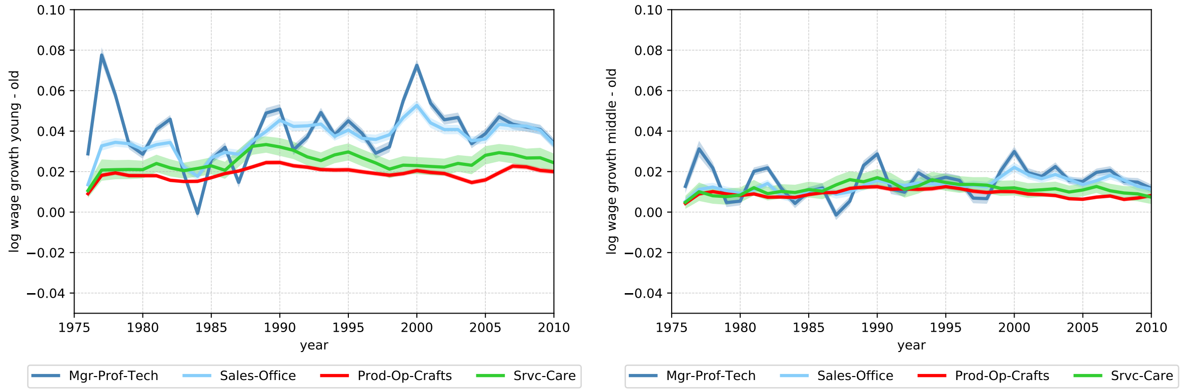
group rise somewhat more over time than in the older group. The qualitative result that task prices polarize, however, remains the same.

D.1.2 Alternative Samples

Different age groups:
One important robustness check is to estimate the model for different age groups. This

Figure A11: Wage growth differences between age groups

(a) $\Delta \log(w)_{[25,34]} - \Delta \log(w)_{[45,54]}$ (b) $\Delta \log(w)_{[35,44]} - \Delta \log(w)_{[45,54]}$



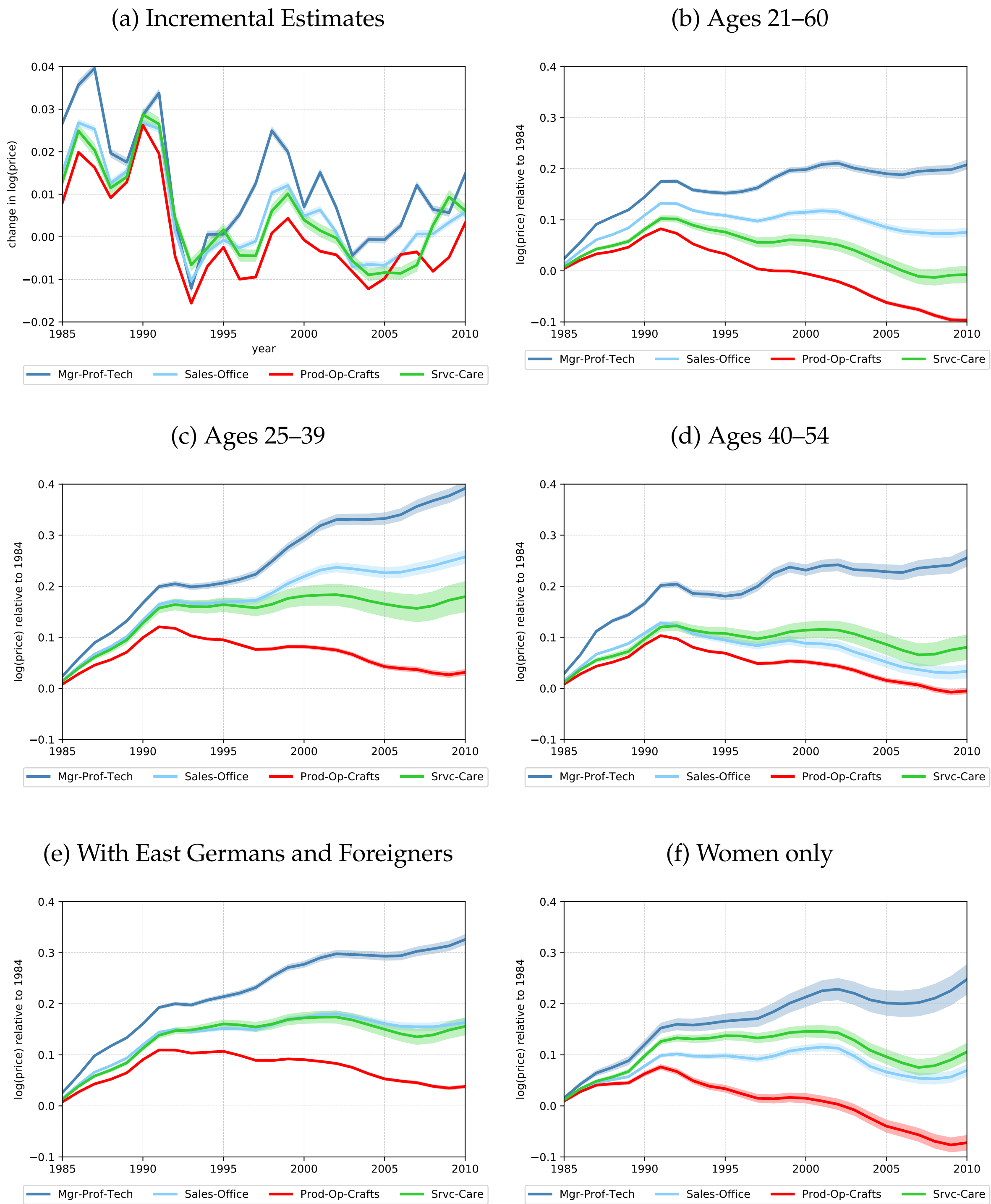
Source: SIAB data, own calculations. The upper two panels show average wage growth of 25-34 (left panel) and 35-44 (right panel) year old profession stayers relative to 45-54 year olds in each profession over time. The lower two panels show the same for profession switchers. Shaded areas are 95% confidence intervals.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

is because, as discussed in detail in Appendix B.2.1, *changing* dynamic considerations in workers' profession choices should arguably not be as important for older as for younger workers. We also saw in the previous subsection evidence for steepening life cycle wage growth within Mgr-Prof-Tech and Sales-Office, which would imply differing task price estimates for these professions in an old versus young sample.

Figure A12 depicts the results from estimating our model on the samples of "younger" workers aged 25–39 and "older" workers aged 40–54, separately, and on the wider ages of 21–60 year olds. We see that task prices rise less in general for the wider 21–60 age range than for our main 25–54 year olds but the evolution of *relative* task prices, which are our focus, appears very similar. Consistent with the evidence in Table 1, relative task prices for the Mgr-Prof-Tech and Sales-Office professions rise more over time in the younger than in the older sample. However, the qualitative result that task prices are polarizing remains the same. Therefore, our task price estimates appear largely robust to the steepening life-cycle profiles in Mgr-Prof-Tech and Sales-Office professions as well as to potentially changing dynamic considerations of workers over time. The latter is also reinforced by similar task price estimates in the sample of women, which we turn to next, as women should arguably also have more muted dynamic incentives than men when choosing professions.

East Germans and foreigners, and women only:
We have restricted our main sample to West German men as these can be defined consistently over the period 1975–2010 and many potentially confounding factors that may have affected women or foreigners, such as higher labor force participation, declining workplace discrimination (e.g., Hsieh et al., 2013), and rapidly rising educational attainment, do not apply. Nonetheless, the entry of women and foreigners as well as the reunification with the East constituted major supply shifts affecting the German labor market during our sample period. If women or foreigners were more inclined

Figure A12: Alternative Estimation Samples



to work in Srvc-Care, for example, rising employment and falling wages in this profession may be due to changes in labor supply. Also, if women or foreigners tend to earn less in certain professions, estimated task prices may be confounded by declines of such wage gaps over time. We therefore examine whether general equilibrium and composition effects due to supply shifts are important by checking whether our estimates differ when we include these groups in our sample.

Figure A12 again shows the results. First, the task prices hardly change when we include males working in East Germany (increases sample by circa 15%) and foreign males (circa 6%) in the estimation. Still more notable, when we estimate our model for women only (circa half of male sample), task prices are qualitatively the same but they polarize even more strongly than in the main sample of males. These results show that composition or general equilibrium effects due to changes in labor supply seem not to have substantially altered our estimates. They also indicate that the same forces that have polarized task prices for men may have been at least as strong for women, potentially dominating other drivers of wages for women in different professions over the last decades.

Different base periods:
In the main estimations, our base period are the years 1975–1984. The evolution of average wages in Figure A18 suggests that this is a good choice given the assumption that relative task prices in the base period should be constant. Nonetheless, we examine whether our results are robust to different choices of base period.

Figure A13 reports task price estimates for different base periods, plotting them *relative* to Prod-Op-Crafts in order to remove differences in general wage growth across periods which are not our focus. We see that estimates using the period 1975–85 are very similar to our main results and that shorter initial base periods (1975-80 and 1975–83) yield more extreme relative task price changes. This is likely due to the fact that relative wage growth in Prod-Op-Crafts was strong during 1975-80. Accordingly, the long base period 1975–90 covering all of the pre-unification era yields substantially smaller relative task price changes than our main estimates. What all the different base periods have in common, however, is that task prices robustly polarize during the subsequent estimation periods. Our main result that task prices polarized over the last decades is therefore robust to the choice of base period and the assumption of constant relative task price changes during that time.

Four- and five-year period length:
We also estimate the model with four- and five-year periods instead of the annual data used for the main results. Such increased period lengths should be informative about whether our findings are generally robust to exploiting relatively short-run wage changes in order to estimate task prices and skill accumulation. For example, if initial wage costs of switching professions are large and potentially changing over time, longer periods may be able to bypass the bulk of these wage drops as argued in Appendix B.2.2. Also, if workers' idiosyncratic skill shocks or learning about skills (e.g., as in Appendix B.2.3) are correlated over time,[37] one-year periods may be too short for estimates not to be confounded by such autocorrelations.

Figure A13 graphs the results from increasing the period length to four and five

[37]The evidence on the existence and importance of correlated wage shocks seems to be mixed (e.g., see Gibbons and Waldman, 1999, and the references therein).

years.[38] We see that, although we need to stop after 2008 as our last four-year period, the results for the former are very similar to our main estimation. The results for the five-year periods require a different base period of 1975–1985. They are very similar to the robustness check with that base period above and the *relative* task prices are therefore also very similar to the main estimation results. We conclude that our findings are robust to longer period lengths and that concerns such as serial correlation of skill shocks or changing wage costs of switching do not appear of first-order importance for our estimates. These results are also reassuring concerning robustness with respect to the treatment of employment and labor force status in our main estimations because longer period lengths should also include more workers who switched professions via an intermittent unemployment spell (see discussion of $\gamma_{k',k,a}$ estimates in Table 2). We now turn to explicit modeling of unemployment and labor force exit.

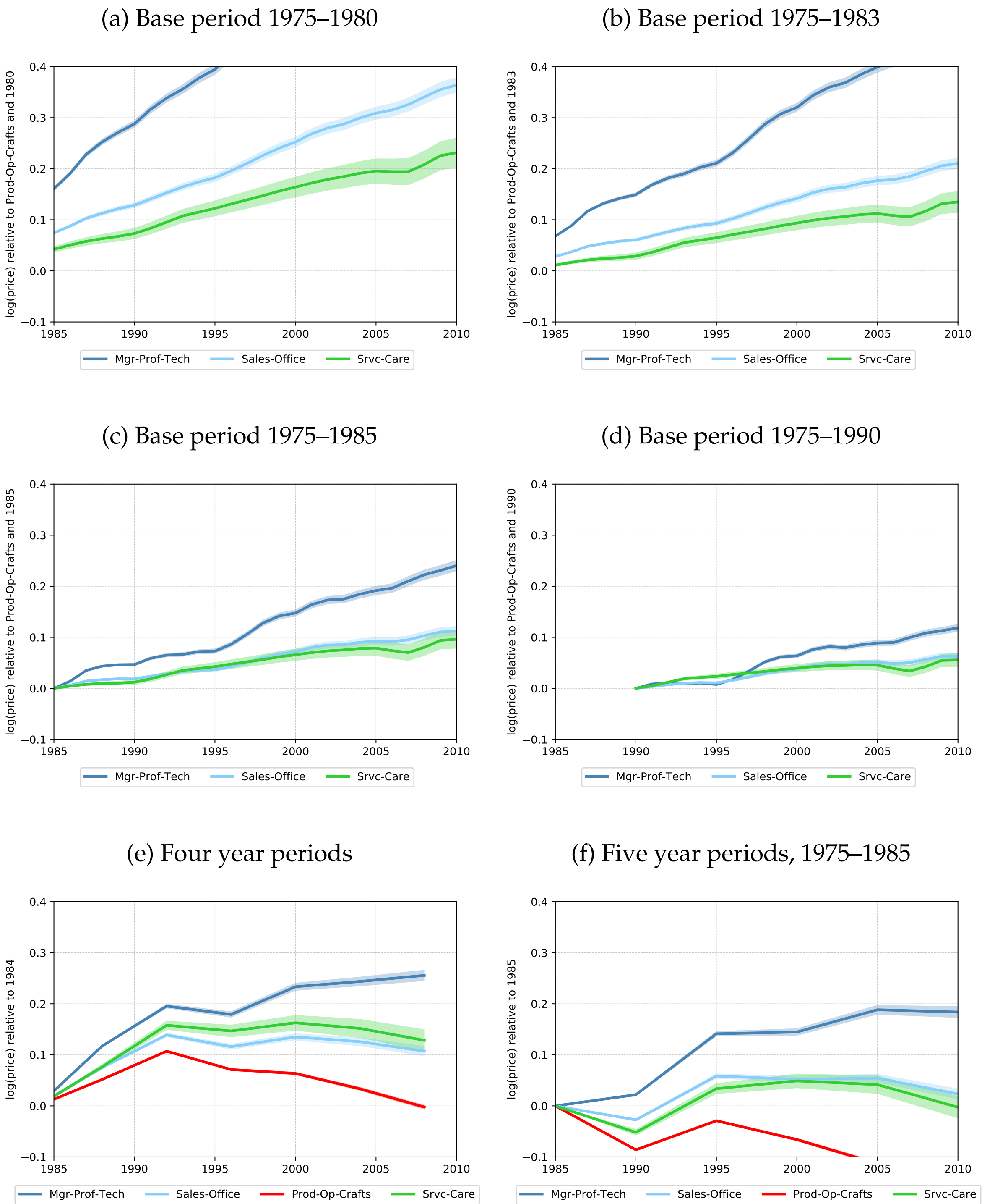
Unemployment and leaving the labor force as a choice:
Another key robustness check is to allow for endogenous unemployment and exit from the labor force. In the main estimation we have assumed that entering and leaving the sample is exogenous. This is obvious for individuals who reach age 25 or 55 (the borders of our sample age range) but it might not be an innocuous assumption during the career. In particular, workers may *choose to* become unemployed or leave the labor force if they obtain a sufficiently bad idiosyncratic skill shock or vice versa for a sufficiently good shock, and if the (time-limited) benefits or other non-labor income they obtain are sufficiently high. This could lead to endogeneity bias in our task price estimates.

In this robustness check, we therefore assume that becoming unemployed or leaving the labor force temporarily is fully endogenous. [39] We do this by imputing workers' wages and their profession choices if they are unemployed or out of the labor force for any number of years between two spells of employment. We impute those by comparing pre and post unemployment/olf wages and assigning them the lower of those two wages adjusted for inflation. That, is we assume that workers could well have worked within the lower paying profession but chose to become unemployed or leave the labor force for some period of time instead. On this sample, which is about 10% larger in size, we then repeat the estimation. The results, depicted in Figure A14 are again almost unchanged, which indicates that exogenous unemployment or leaving the labor force is not a critical assumption in our model.

[38] We drop all the years which are not a multiple of 4 relative to the base period 1984 and so keep 1976, 1980, 1984, 1988 and so on. Wage growth and profession choice indicators are then calculated on the basis of these 4 year periods, i.e., the wage growth refers to the growth between 1988 and 1992, for instance. To avoid having only one point of data within the base period and therefore estimating the skill accumulation from differences between 1975 and 1980 only, we use 4 years. We also repeat the exercise using 5 year periods and 1975–85 as the base period.

[39] The reality is likely somewhere in between these two extremes. We do maintain the assumption that permanently leaving employment is exogenous because for prime age males this is quite rare (roughly 1.1% each year as opposed to 2.3% for temporary unemployment) and likely often due to relatively exogenous factors such as illness/death, moving to East Germany or abroad, becoming self-employed or civil servant, etc..

Figure A13: Alternative Estimation Samples



D.1.3 Alternative Specifications

Education and task-specific skill accumulation:
In the main estimation, skill accumulation varies by combination of current and last year's profession as well as by age in order to account for the different life-cycle wage

Table A20: Estimates for $\gamma_{k',k,a}$ with filled unemployment

k'	k	[25, 35)	[35, 45)	[45, 55)
Mgr-Prof-Tech	Mgr-Prof-Tech	0.041	0.013	-0.002
	Sales-Office	0.182	0.026	-0.071
	Prod-Op-Crafts	0.089	-0.058	-0.149
	Srvc-Care	0.184	-0.101	-0.234
Sales-Office	Mgr-Prof-Tech	0.362	0.082	0.013
	Sales-Office	0.040	0.015	0.002
	Prod-Op-Crafts	0.133	0.006	-0.094
	Srvc-Care	0.189	-0.106	-0.205
Prod-Op-Crafts	Mgr-Prof-Tech	0.482	0.124	0.031
	Sales-Office	0.262	0.069	-0.034
	Prod-Op-Crafts	0.019	0.008	0.000
	Srvc-Care	0.051	-0.073	-0.118
Srvc-Care	Mgr-Prof-Tech	0.821	0.234	0.081
	Sales-Office	0.406	0.171	-0.005
	Prod-Op-Crafts	0.233	0.093	0.022
	Srvc-Care	0.020	0.006	-0.003

Source: SIAB data, own calculations. The table shows the estimated $\hat{\gamma}_{k',k,a}$ for age groups a. The first k represents the current profession whereas k' denotes the former profession. Intermittent unemployment gaps were filled up as described in the text. *Legend:* Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

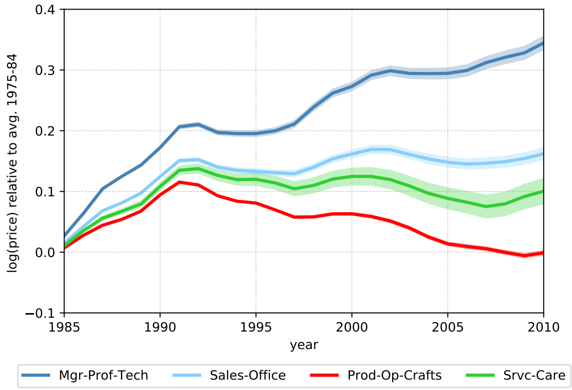
facts documented in Section 2.3. In this robustness check we also allow for the fact that skill accumulation may additionally vary by the worker's education level and by the analytical, interactive, routine, and manual tasks performed in the 120 detailed occupations within professions.

Figure A14 depicts the results. First, we interact the $\gamma_{k',k,a}$ in skill accumulation Equation 7 by high (university or college degree), medium (apprenticeship or Abitur), and low (without postsecondary) education level of the worker. Second, we linearly interact $\gamma_{k',k,a}$ with the four continuous task measures. The task prices are in both cases almost exactly the same as in our main estimations. Therefore, our results are robust to such richer specifications of the skill accumulation function.

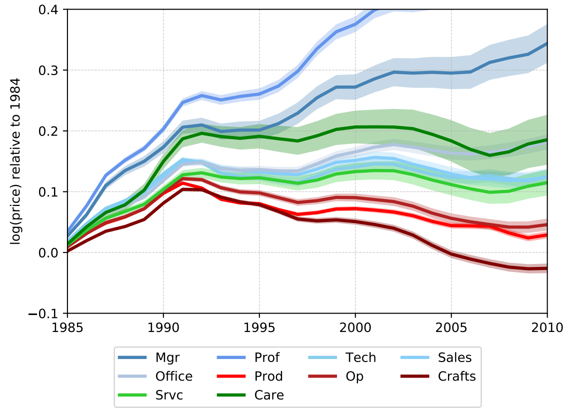
More detailed professions:
We argued above that Mgr-Prof-Tech, Sales-Office, Prod-Op-Crafts, and Srvc-Care constitute an attractive classification of professions for our purposes, as it reflects a clear delineation along occupational task content (Table A2) and adopts other common occupational groupings in the literature to the German case (e.g., Acemoglu and Autor, 2011; Cavaglia and Etheridge, 2017, the latter also use German data). Nonetheless, to check whether the broad polarization of task prices may have been driven by our occupational grouping, we re-estimate the model using ten more detailed subprofessions.

Figure A14: Alternative Estimation Specifications

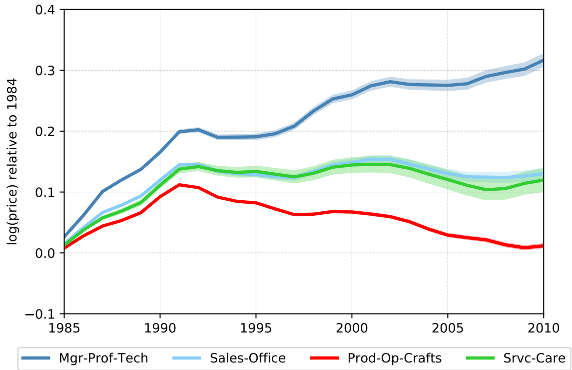
(a) Unemployment and OLF



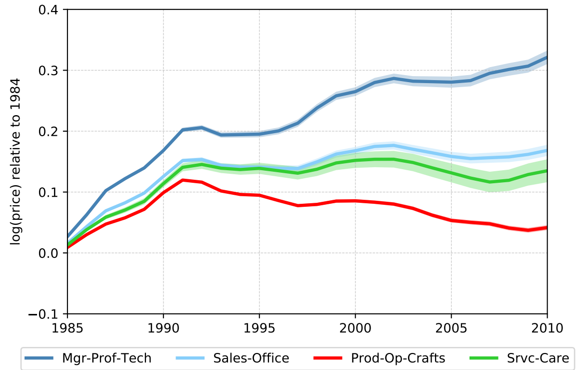
(b) Ten professions



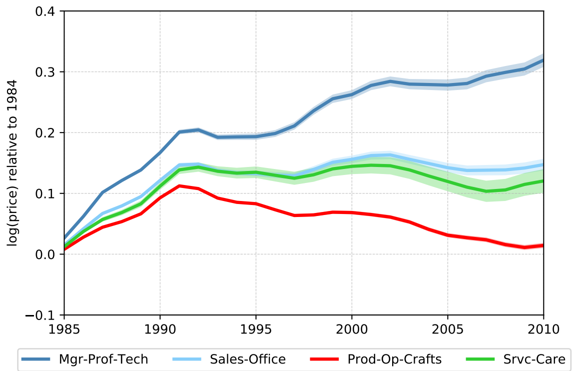
(c) Including Education



(d) Including Task Measures



(e) IV



(f) Fixed Effects

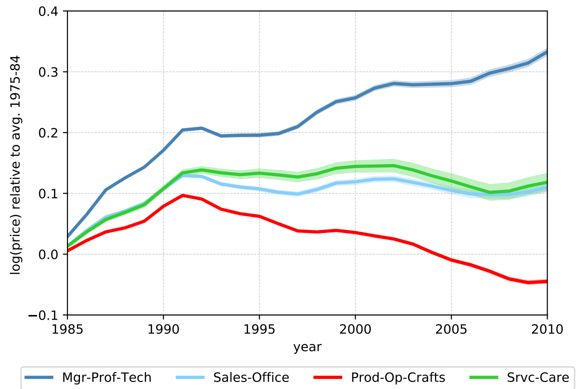


Figure A14 again shows the results. The growth in task prices is remarkably similar for these sub-professions, which supports our occupation groups. In particular, managerial and professional task prices within Mgr-Prof-Tech rise strongly; sales and office within Sales-Office as well as services and care within Srvc-Care experience modest task price growth; and the constituting components of Prod-Op-Crafts all see their task prices fall compare to every other sub-profession. These findings show that our main results do not depend on the choice of grouping into the four broad professions. They also illustrate the ease of our method to estimate task prices for many professions.

Instrumental variables estimation:
In Section 3.2 we argued that our main estimation using the fully saturated model for skill accumulation across profession combinations largely accounts for endogenous switches due to idiosyncratic skill shocks. We also discussed an alternative estimation method, which instruments endogenous current period professions using exogenous last period professions.

Figure A14 reports the results from this instrumental variables (IV) estimation.[40] The task prices as well as the average skill accumulation are almost identical to our main estimation. Sections B.1 and C.1 showed formally and using Monte Carlo simulations, respectively, that both the fully saturated model as well as the IV should give us a lower bound to the absolute changes in task prices relative to the reference profession (Prod-Op-Crafts). Therefore, these results make us confident that actual task prices polarized at least as strongly as shown in our main estimation results.

Fixed effects estimation:
We also compare our results to the alternative estimation method using fixed effects. As discussed in Appendix B.3, even without idiosyncratic skill shocks, the fixed effects requires detailed controls of worker's entire labor market history. With idiosyncratic skill shocks, the bias is potentially large and cannot in general be signed, which is illustrated in the Monte Carlo simulations of Appendix C.4. Nonetheless, it should be supportive of our empirical results if this alternative estimation approach yielded qualitatively similar findings.

Once more, Figure A14 graphs the results from the fixed effects estimation. The task prices widen much more strongly than in our main estimation and skill accumulation continues to increase over the whole life-cycle (it is hardly concave and almost linear, even at ages 45–54). The fact that task prices for the high skill accumulation Mgr-Prof-Tech and Sales-Office professions rise substantially faster in the fixed effects than the main estimation method is consistent with the results from our Monte Carlo simulations, even in the absence of skill shocks (see Figure A8). These suggested that task price growth in the fixed effects, as it is usually implemented, is confounded by skill accumulation and therefore overestimated for the high skill-growth professions. Footnote 31 in Appendix B.3 provides a somewhat informal economic explanation. Nonethe-

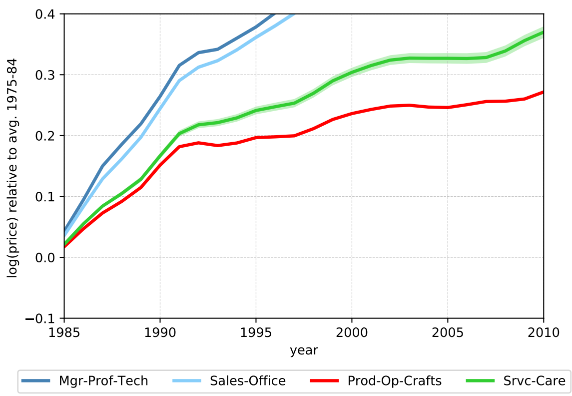
[40] As discussed in Section 3.2, we can only estimate the skill accumulation for each of four average task choices, since we only have four instruments. That is, we reduce Equation (7) to $\Delta s_{k,i,t} = \sum_{k'=1}^{K} \sum_{a=1}^{A} I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a] \cdot \gamma_{k',a} + v_{i,t}$ so that the estimation Equation (8) becomes

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta\pi_{k,t} + \sum_{k=1}^{K} \sum_{a=1}^{A} \bar{I}_{k,i,t} I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a] \cdot \gamma_{k',a} + u_{i,t},$$

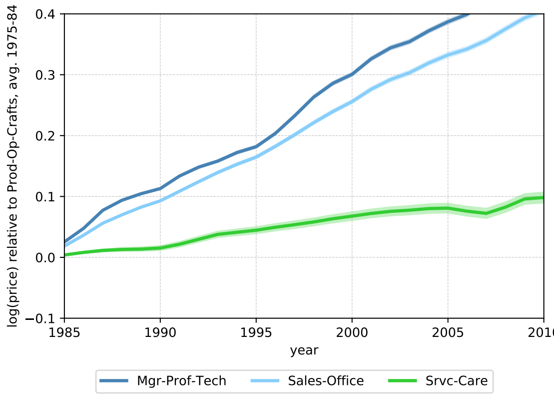
with $\bar{I}_{1,i,t}I_{1,i,t-1}, \bar{I}_{2,i,t}I_{2,i,t-1}, \bar{I}_{3,i,t}I_{3,i,t-1}, \bar{I}_{4,i,t}I_{4,i,t-1}$ instrumented by $I_{1,i,t-1}, I_{2,i,t-1}, I_{3,i,t-1}, I_{4,i,t-1}$, both interacted with the age dummies.

Figure A15: Estimated task prices without skill accumulation controls and with fixed effects using profession-specific experience profiles

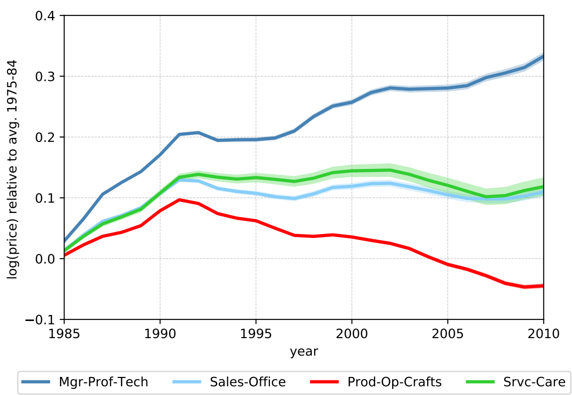
(a) Our Method without Skill Accumulation



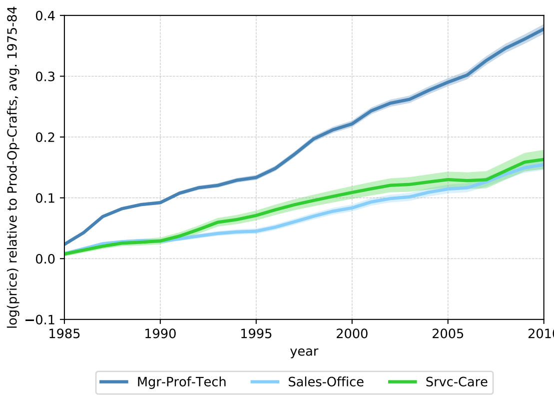
(b) Our Method without Skill Accumulation



(c) Fixed Effects with Prof.-Specific Profiles



(d) Fixed Effects with Prof.-Specific Profiles



Source: SIAB data, own calculations. The top left panel shows the estimated cumulated task price changes over time normalized to zero in 1984 without controlling for differences in skill accumulation. The lines in the right panel were computed by subtracting the cumulated price changes of Prod-Op-Crafts from the other prices. The bottom row of the Figure shows the estimates from a fixed effects estimation controlling for profession-specific experience profiles, i.e. regression Equation (28). Shaded areas represent the 95% confidence intervals computed by adding up the standard errors of price changes and their covariances. Standard errors are clustered at the individual level. The price were estimated using the main sample of full-time male workers, aged 25 - 54, dropping permanent foreigners as well as spells from East Germany.
Legend: Mgr-Prof-Tech: managers, professionals, and technicians; Sales-Office: sales and office; Prod-Op-Crafts: production, operators, and craftsmen; Srvc-Care: services and care.

less, the estimated task prices also polarize in the fixed effects approach, which lends further support to our main empirical results in this paper.

No skill accumulation controls:
Finally, to top row of Figure A15 shows absolute and relative task prices if we do not control for differences in skill accumulation between the professions. As discussed in the main text, the estimates without skill accumulation are likely not only to overestimate the growth in absolute task prices for all professions but also for the high skill accumulation Mgr-Prof-Tech and Sales-Office relative to the Prod-Op-Crafts and Srvc-Care professions. We see that this is exactly what happens and it looks strikingly similar to the fixed effects estimation with profession-specific experience profiles (i.e.

regression Equation (28)) depicted in the bottom row of the Figure. This suggests that the latter specification largely ignores important aspects of skill accumulation as discussed in Section B.3. In our comparison to the fixed effects estimation approach we therefore focus on the specification with profession-specific tenure profiles as discussed above. The Monte Carlo simulations of Section C, however, show that also this specification is unable to fully account for workers' diverse skill accumulation profiles and therefore unable to estimate the correct task prices.

D.2 Alternative Decompositions of Skill Selection

This section provides an alternative decomposition of the changing skill selection to Section 5. It also presents a version of Figure 9 including switches with intermittent unemployment or exit from the labor force and with initial skill endowments calculated using the estimated skill accumulation parameters.

We start by decomposing the skills plotted in Figure 7 based on leavers' marginal selection instead of entrants:[41]

$$\begin{aligned} \mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = \; & \underbrace{\left(1-h^{ent}_{k,t}\right)\cdot \mathrm{E}[\Delta s^{sty}_{k,i,t}]}_{\textbf{learn}\text{ing: accumulation of stayers}} \\ & + \underbrace{h^{ent}_{k,t}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\textbf{churn}\text{ing: difference entrants, leavers}} \\ & + \underbrace{\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\cdot\left(\mathrm{E}[s^{lvr}_{k,i,t-1}-\mathrm{E}[s^{sty}_{k,i,t-1}]]\right)}_{\textbf{marg}\text{inal }\textbf{sel}\text{ection}} \end{aligned} \tag{36}$$

Here, superscript sty indicates a profession stayer, lvr a leaver, and ent an entrant. $h^{lvr}_{k,t-1}$ indicates the share of last period's workers in k who left the profession in this period and $h^{ent}_{k,t}$ the share of this period's workers who entered this period.

The results from conducting the decomposition this way are depicted in Figure A16. We see that the marginal selection effect tends to be smaller than in the main text, which reflects the fact the difference between wages of leaver and stayers are smaller (relative to Prod-Op-Crafts) than between entrants and stayers. Nonetheless, as shown in Figure 2, these differences are negative and substantial. Furthermore, also the marginal selection effect in Figure A16 is sizable.

A middle-ground between the decompositions based on entrants (Figure 11) and

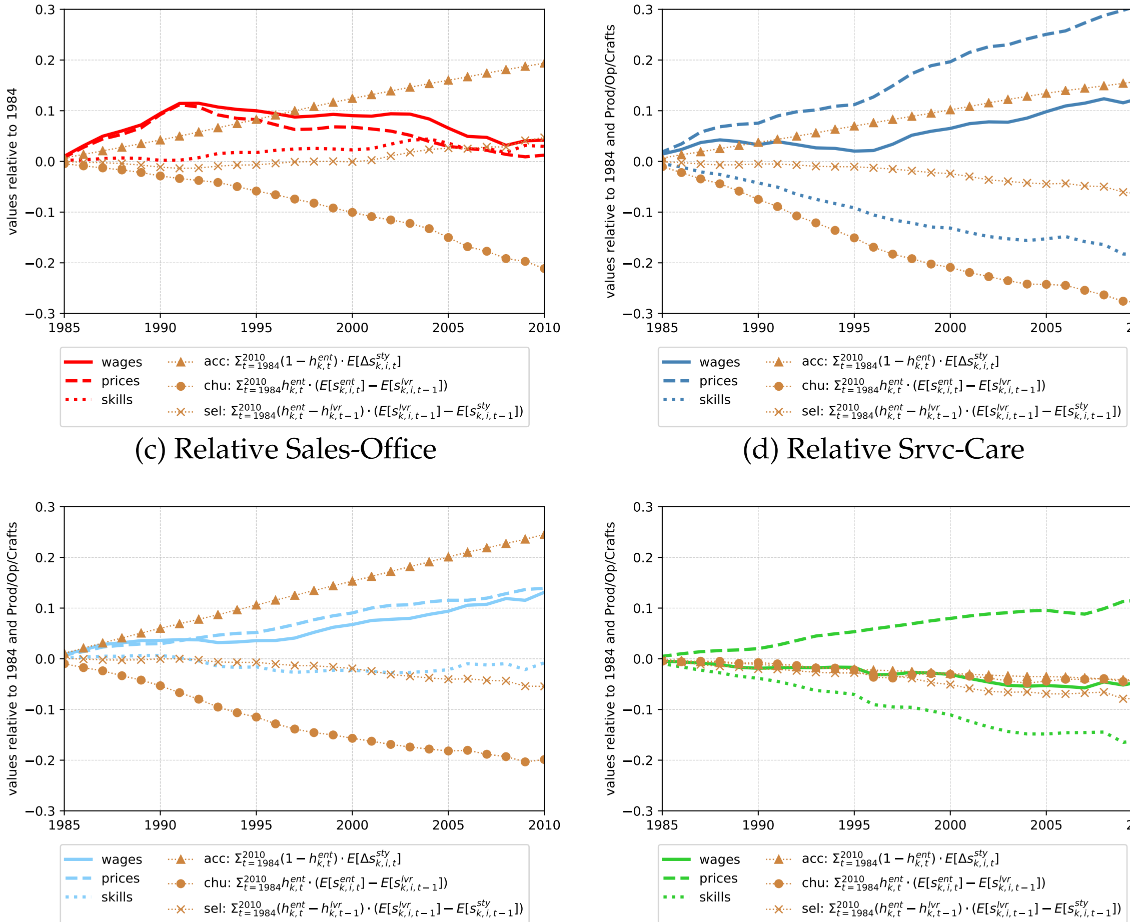
[41] The intermediate steps are $\mathrm{E}[(1-h^{ent}_{k,t})s^{sty}_{k,i,t}+h^{ent}_{k,t}s^{ent}_{k,i,t}]-\mathrm{E}[(1-h^{lvr}_{k,t-1})s^{sty}_{k,i,t-1}+h^{lvr}_{k,t-1}s^{lvr}_{k,i,t-1}] =$

$= (1-h^{ent}_{k,t})\mathrm{E}[\Delta s^{sty}_{k,i,t}]+\left(h^{lvr}_{k,t-1}-h^{ent}_{k,t}\right)\mathrm{E}[s^{sty}_{k,i,t-1}]+h^{ent}_{k,t}\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)+\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\mathrm{E}[s^{lvr}_{k,i,t-1}]$.

Figure A16: Alternative Decomposition of Skills into Accumulation, Churning, and Marginal Selection (Based on Leavers)

(a) Prod-Op-Crafts (b) Relative Mgr-Prof-Tech

(c) Relative Sales-Office (d) Relative Srvc-Care



leavers (A16) could be this "average decomposition" of Equations (11) and (36):

$$
\begin{aligned}
\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1] - \mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = & \underbrace{[1-\frac{1}{2}\left(h_{k,t-1}^{lvr}+h_{k,t}^{ent}\right)] \cdot \mathrm{E}[\Delta s_{k,i,t}^{sty}]}_{\text{1 \textbf{learn}ing: accumulation of stayers}} \\
& + \underbrace{\frac{1}{2}\left(h_{k,t-1}^{lvr}+h_{k,t}^{ent}\right) \cdot \left(\mathrm{E}[s_{k,i,t}^{ent}] - \mathrm{E}[s_{k,i,t-1}^{lvr}]\right)}_{\text{2 \textbf{churn}ing: difference entrants, leavers}} \\
& + \underbrace{\frac{1}{2}\left(h_{k,t}^{ent}-h_{k,t-1}^{lvr}\right) \cdot \left(\mathrm{E}[s_{k,i,t}^{ent}] - \mathrm{E}[s_{k,i,t}^{sty}] + \mathrm{E}[s_{k,i,t-1}^{lvr}] - \mathrm{E}[s_{k,i,t-1}^{sty}]\right)}_{\text{3 \textbf{marginal sel}ection}}
\end{aligned}
$$

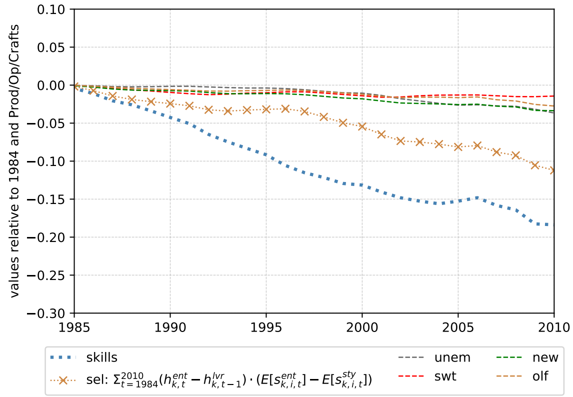
As discussed in the main text, this would come to the conclusion that the marginal selection effect more than fully explains the changing relative skill composition of the Sales-Office profession and a substantial part of Mgr-Prof-Tech and Srvc-Care's changing relative skill composition.

Finally, we provide an alternative decomposition to Figure 9 of the sources of the marginal selection effect. The left panels of Figure A17 show the contributions of new entrants and profession switchers when the latter are split up into direct switchers (as in our main analysis) and switchers with intermittent unemployment or exit from the labor force (as in robustness Section D.1.2). We see that the contribution of the latter group to the marginal selection effect is quite substantial.

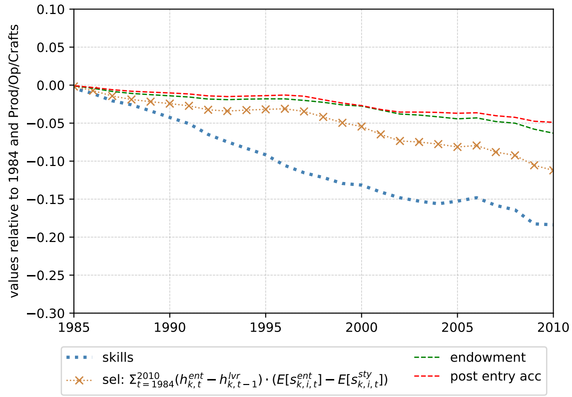
The right panels of Figure A17 uses an alternative estimate to Equation (13) for the decomposition of the marginal selection effect due to endowments versus skill accumulation of stayers. In particular, we use only the estimated systematic accumulation ($s^{sty}_{k,i,t} - s^{sty}_{k,i,t-x_{i,t}} = \sum_{\tau=1}^{x_{i,t}} \sum_{a=1}^{A} I_{k,i,t-\tau} \cdot \mathbb{1}[\text{age}_{i,t-\tau} \in a] \cdot \hat{\gamma}_{k,k,a}$) and thus exclude idiosyncratic skill shocks. Though somewhat less important, the skill accumulation component still explains half of the marginal selection effect in Mgr-Prof-Tech and Sales-Office and a non-negligible part in Srvc-Care.

Figure A17: Alternative Decomposition of the Marginal Selection Effect

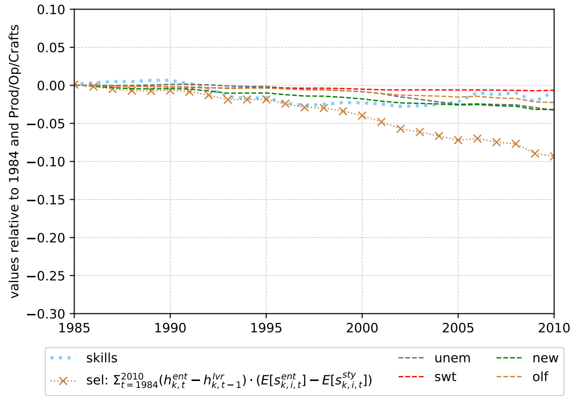
(a) Groups - Mgr-Prof-Tech



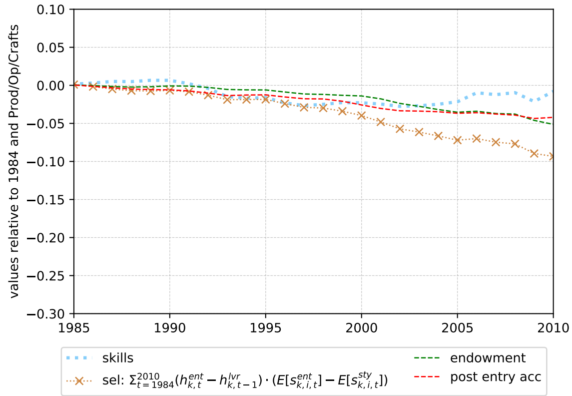
(b) Acc vs Ent - Mgr-Prof-Tech



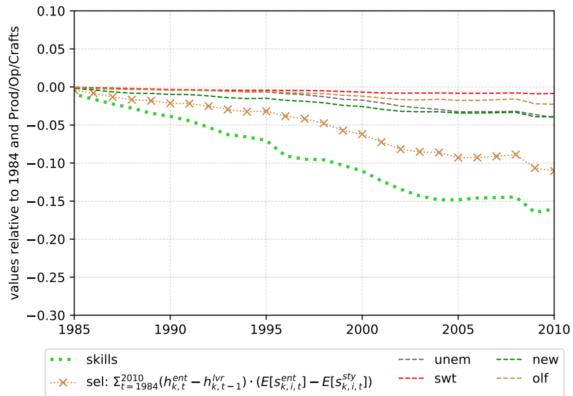
(c) Groups - Sales-Office



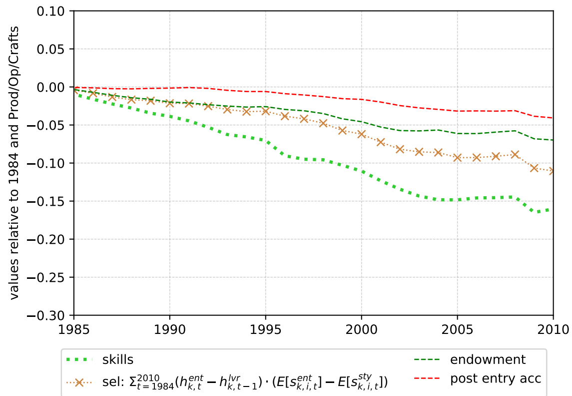
(d) Acc vs Ent - Sales-Office



(e) Groups - Srvc-Care



(f) Acc vs Ent - Srvc-Care

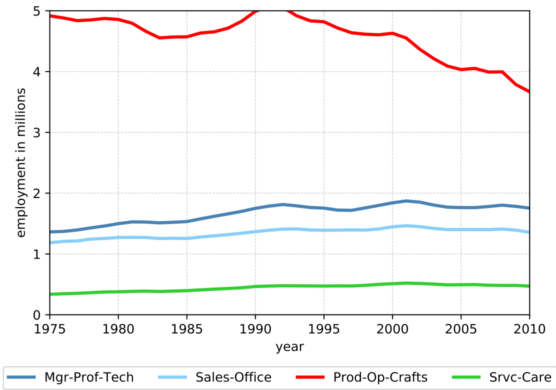


Source: SIAB data, own calculations.

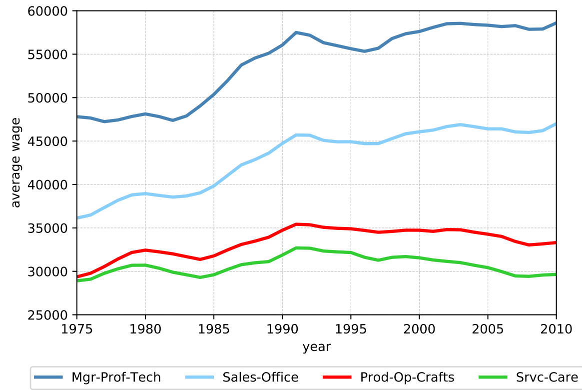
D.3 Additional Figures

Figure A18: Further Evidence on Employment and Wage Trends

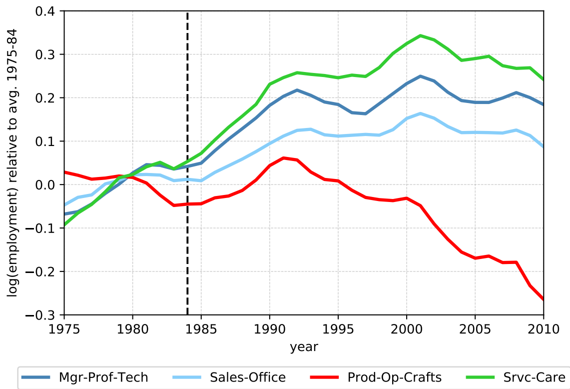
(a) Employment (not normalized)



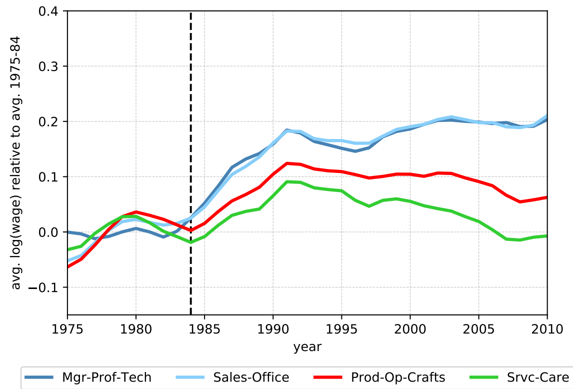
(b) Average log Wages (not normalized)



(c) Employment (incl. base period)



(d) Average Log Wages (incl. base period)



(e) Growth at Percentiles

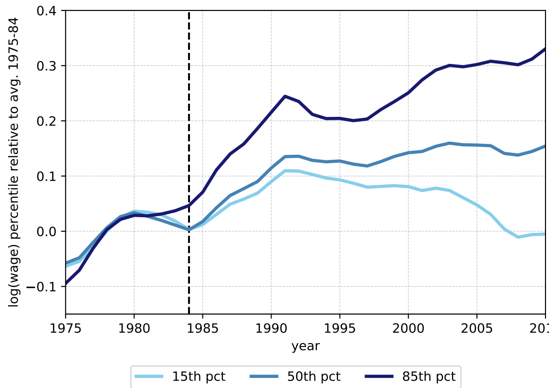


Figure A19: Decomposition of Skills into Accumulation, Churning, and Marginal Selection (All Absolute!)

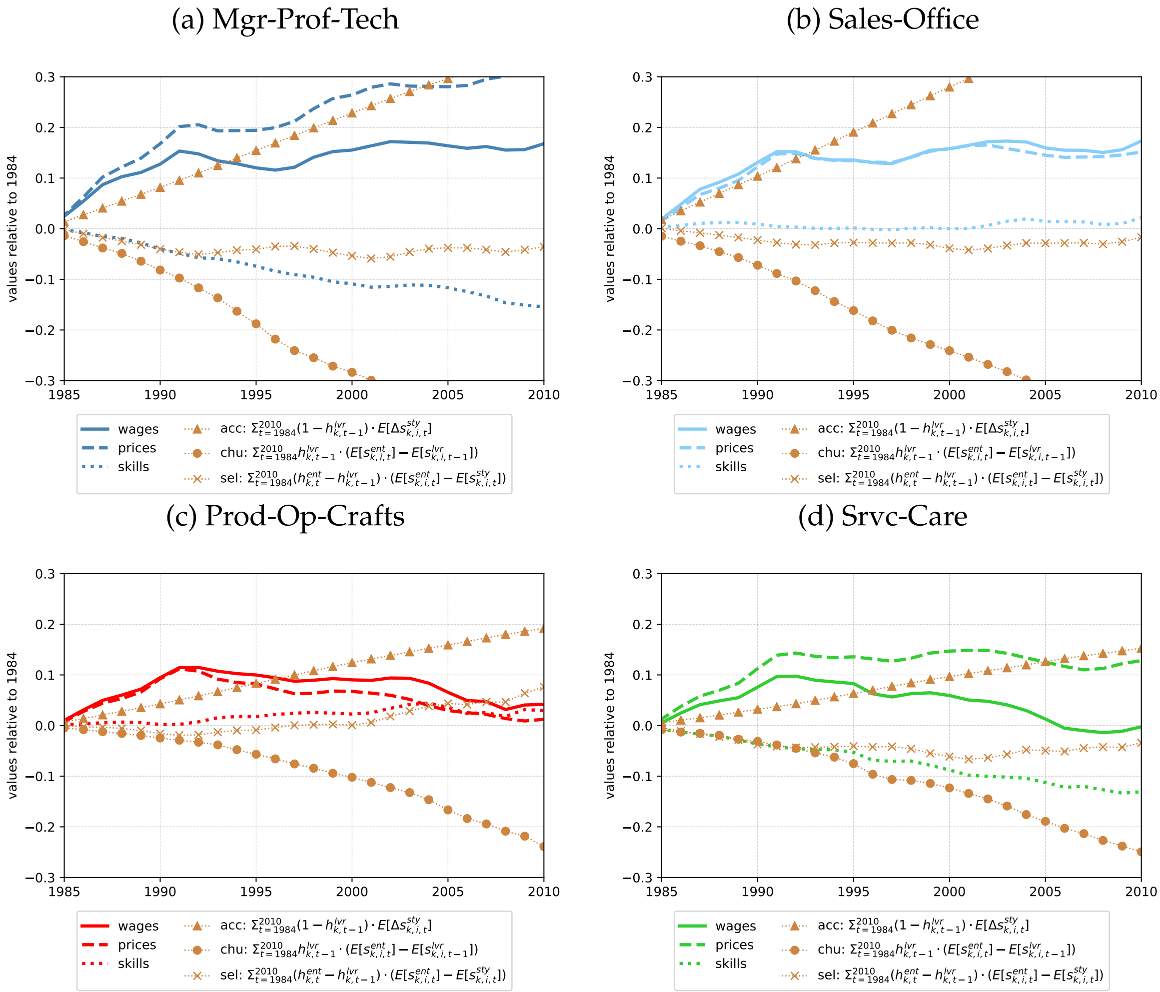
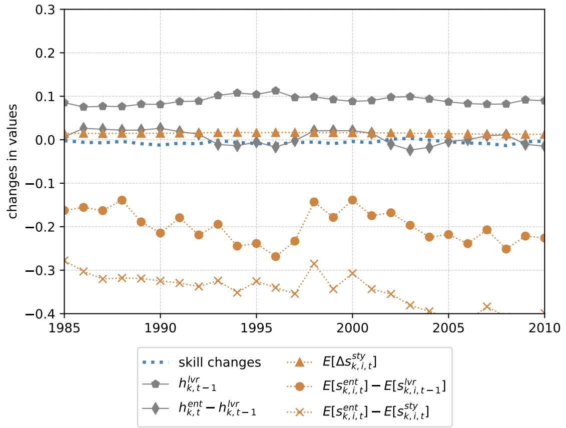
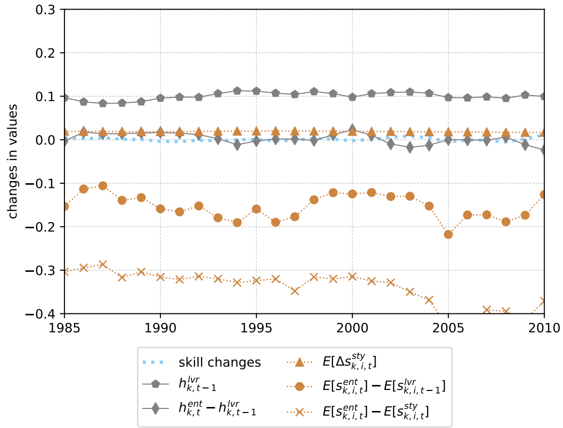


Figure A20: Elements of Decomposition (11) Incrementally

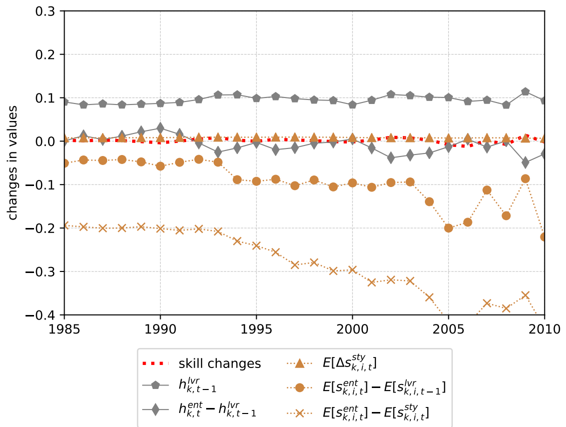
(a) Mgr-Prof-Tech



(b) Sales-Office



(c) Prod-Op-Crafts



(d) Srvc-Care