The Polarization of Task Prices in Germany, 1985–2010

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PRELIMINARY

Abstract

We propose a new method to estimate changing task prices and skill accumulation across multiple sectors. The method exploits workers' wage growth in panel data, allowing for an arbitrary multidimensional distribution of skills and endogenous switching due to skill shocks. We apply our method to German administrative records and find that the prices for work in high-skill as well as low-skill professions strongly increased compared to middle-skill professions. We empirically identify a new selection effect that afflicts rising and benefits shrinking sectors: entrants as well as leavers to any profession are less skilled than stayers and rising (shrinking) professions feature positive (negative) net entry. This has held back average wages in high-skill professions and it even overturned the rising task prices in low-skill professions in our data.

Keywords: Task prices; Multisector Roy Model; Wage Inequality; Routine-Biased Technical Change; German Administrative Panel Data
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1 Introduction

Over the last decades the employment as well as the wage structures of developed countries have shifted drastically, with employment polarizing and at the same time wages becoming more unequal across the board (e.g. Acemoglu and Autor, 2011). This had led to an active debate about what are the drivers of such changes, including but not limited to technology, international trade, or 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 of skills taking place. For example, recent research has documented rising labor productivity but at the same time shrinking workforce in the manufacturing sector (Young, 2014) or rising employment in high- and low-skill 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). The literature has suspected that these findings may be due to selection effects, that is, due to low skills of new entrants into growing sectors or occupations. It has then estimated cross-sectional (Firpo et al., 2013; Young, 2014; Gottschalk et al., 2015; Böhm, 2017) or panel models with individual fixed effects (Cortes, 2016; Cavaglia and Etheridge, 2017) to correct for such selection effects.

However, workers' skills are not constant over time. They systematically accumulate within different professions as well as changing idiosyncratically, especially when individuals switch between sectors. Therefore, selection effects in the data are to a substantial extent endogenous to workers' past and current job choices, and cannot easily be controlled for by including time-invariant fixed effects or standard experience controls. This also applies to different cross-sections of workers, as in each point in time these feature varying selection effects due to different overall skill accumulation.

In our paper, we provide a new method for estimating task prices (i.e. selection-corrected wages) in panel data, which flexibly takes the systematic and idiosyncratic time-varying accumulation as well as time-constant skill differences into account. The method retains the strength from fixed effects and standard regression analysis that it can be implemented for multiple sectors and any general distribution of worker skills and skill shocks. It is also transparent in which basic moments of the data are used for identification.

Applying our method to high-quality administrative panel data from Germany, we find that task prices have strongly polarized during the last three decades. That is, employment and wages cleaned of composition effects have evolved consistent with rising demand for high-skill and low-skill relative to middle-skill professions.[1] We then use independent evidence to show that important skill composition effects in fact *result from* changing sector size: if marginal workers have lower (whether constant or time-varying) skills than incumbents in a sector, net entry will lead to a deteriorating skill selection and vice versa for net exit.

We quantify the contributions to the differences in skills of profession entrants versus incumbents and of leavers versus stayers, and find that a substantial part of them are due to profession-specific accumulation rather than workers' initial skill endowments. This underscores the importance of differential skill accumulation for generating the large selection effects afflicting growing sectors the we observe in the data.

We start by presenting two sets of stylized empirical facts. As mentioned above, the German employment structure polarized during the period of 1985–2010, but the wage structure widened overall and in particular wages fell in strongly growing low-skill services professions. At the same time, average wages of entrants as well as leavers of every profession are substantially lower than of incumbents or stayers. We show that together with the high rate of net entry into (exit from) the growing (shrinking) professions, this could lead to substantial composition effects.

The second set of empirical facts indicates that accounting for worker skill changes over the career is critical when evaluating such composition effects or when estimating the task prices for professions. That is, workers have systematically and substantially different wage growth depending on observable characteristics, in which professions they start out, and on their profession-specific experience during the life-cycle, even conditional on current jobs. There also exists striking idiosyncratic heterogeneity of wages within the same detailed career paths.[2]

We then provide a new model to estimate task prices that is able to account for these stylized facts in the data. The model has two key features. First, it allows for general worker self-selection across professions by using a result from Böhm (2017) that tightly relates changes in workers' observed wages to changes in their potential wages (prices plus skills in logs) and their (changes in) profession choices. This brings the analysis to first differences, which yields an important advantage to flexibly account for skill accumulation as one need not control for workers' full labor market history. Instead detailed controls for previous period profession choices and worker character-

[1]We term broad occupation groups based on measured job task content that encompass managerial, professional, and technical; sales and office (both high-skill); production, operator, and crafts (middle-skill); and elementary services (low-skill) as our four 'professions'.

[2]In particular, wages systematically differ ex ante and they change ex post for workers who switch to other professions (i.e., higher and rising for high-skilled destination professions; lower and falling for all others).

istics suffice.

One potential limitation of our estimation method is that we need a pre-period (1975–1984 in the SIAB 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 in the main period compared to the pre-period. In many applications this is what one would be interested in.[3]

The other potential limitation are the above-mentioned idiosyncratic wage changes, which systematically covary with workers' switches of professions. This generates a potential endogeneity bias of 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 on only past job choices, largely account for the endogeneity. In fact both provide a lower bound to the true absolute changes in task prices.

We further provide extensive Monte Carlo simulations generating data as similar as possible to the SIAB and showing that our method identifies the correct task prices (or their accelerations/decelerations) under a rich model for systematic skill accumulation, and that it provides tight lower bounds when idiosyncratic skill shocks are included.[4] An approximation we make for the general worker self-selection result is innocuous.

We estimate the model in the SIAB data during 1985–2014. Four different occupation groups ('professions') based on their measured job task content are used: managerial, professional and technical (MPT); sales and office (SO); production, operator, and crafts (POC); and elementary services.[5] Our statistically precise estimates show that task prices strongly polarized in the sense that high-earning non-routine analytical (MPT) and interactive (SO) as well as low-earning non-routine manual (services) prices increased compared to routine manual (POC) task prices. The estimated task prices imply negative composition effects for all three rising professions, but especially for services whose average wage changes are even turned around to be negative by the

[3]We verify in our data that the (shape of) the skill accumulation function has not changed after the pre-period. We also vary the period length (one-year and five-year periods are reported below), which should lead to different results if non-pecuniary payoffs, switching costs, or serial correlation of idiosyncratic skill shocks that are not in our model are quantitatively important. Finally, since we use a model with static decisions in a panel data setting, we ensure that our estimates are similar across different age groups (who are likely to value dynamic human capital considerations differentially).

[4]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 effectively breaks down with idiosyncratic skill shocks.

[5]We also estimate the model for the nine more detailed sub-professions and get the same results.

selection effect.

Next we decompose each profession's skill change into accumulation (share of stayers in a profession times their skill growth over the period), churning (share of leavers times difference in skills between entrants and leavers), and marginal selection (net entry times wage difference between stayers and entrants or leavers). It turns out that a large share of the skill composition change implied by the task prices is due to marginal selection effect, which was singled out before as a key stylized fact of the data above and which is zero if sector does not grow. Since it does not depend on task prices, this provides independent evidence from the estimates that the direction and size of their implied selection effects are plausible. Therefore, the skill selection into a profession deteriorates *because* its task prices increase and its employment grows.

We decompose this marginal selection effect further into differences in skill endowments between incumbents or stayers versus entrants or leavers and differences in skill accumulation. That the latter difference is strong and quantitatively at least as important than the former underscores the importance of detailed accounting for skill accumulation in our analysis. It also supports the plausibility of the very substantial selection effects that we uncover. This last result implies the selection effect is strong but partly temporary: once the sector stops growing and net inexperienced worker entry stops, the selection effect will revert toward only the time-invariant skill differences between the professions (less than 50 percent of the overall). The increase in average wages of the formerly growing professions therefore continues for some time, albeit at constant employment during that period.

The other counterfactual analyses we provide in the paper is if task prices had never changed (no shifts in employment shares and thus no selection effect, neither temporary nor permanent) and if they had changed at different strengths, which depends on an estimate of the effect on the net inflow and the relative skills of the inflowing workers. This underscores that the selection effects are caused by the induced sector size changes and work exactly in the opposite direction of the task prices.

This 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 changes in the occupation (via routine-biased technical change 'RBTC') and industry (via structural transformation) structure have employed various 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) also in the context of RBTC (Cortes, 2016; Cavaglia and Etheridge, 2017) and when examining skill selection into sectors 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-invariant worker differences as well as rich skill accumulation over the career.[6] 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 sector growth *causes* deteriorating skills and how this effect can be very large, at least temporarily. Both of these arguments rest on workers' sector-specific skill accumulation, which makes up more than 50 percent of the selection effect in any given cross-section in the data. Our estimation method explicitly accounts for this and therefore we are able to fully explain the seemingly contradicting trends in sectoral employment and wages.

The paper proceeds as follows. The next section provides the core motivating 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 our new method for estimating changing task prices in panel data. Section 4 reports the empirical results and analyses the negative skill selection effect on growing sectors. Extensive robustness checks are summarized in Section 5 and the last section concludes.

2 Stylized Facts

2.1 Data

For the empirical analysis, we make use of German social security records - the SIAB Scientific Use File, provided by the IAB. 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 and individuals performing military service. Most notably, it contains

[6] 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).

an individual's full employment history, the occupation, wage, and some sociodemographics. The data is exact to the day as employers need to notify the employment agency if the employment relationship changes.

The main dataset is restricted to full time working 25 to 54 year old German men working in former West-Germany. To the greatest extent, we prepare the data including the wage variable similar to Dustmann et al. (2009) and Card et al. (2013). We provide a more detailed description of the data in appendix F.

2.2 Sectoral Trends

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 professions.

Panel (a) of Figure 1 shows that, in line with other major economies (e.g. Goos and Manning, 2007; Acemoglu and Autor, 2011), Germany has experienced a strong polarization of its employment structure over the last decades. In particular, the employment share of production, operator, and crafts occupations declined by more than ten percentage points during our sample period (1985–2014), while employment in managerial, professional, and technical, sales and office, and services occupations increased.[7] These trends are termed polarization, because production, operator, and crafts are located in the middle of the occupational wage distribution (Panel (b) of Figure A10 in the Appendix) and because employment more generally rose at the fringes of the occupational wage distribution while it fell in the middle (Panel (c)).

The polarization of the employment structure, at least after the mid-1990s, coincided with a dramatic widening of the wage structure. In particular, previous papers have shown that overall wage inequality in Germany strongly increased after 1991. This is depicted in Appendix Figure A10, Panel (d), for our data and very similar to evidence in Dustmann et al. (2009) and Card et al. (2013). In addition, Panel (b) of Figure 1 shows that relative wages in high-paying managerial and sales professions increased and they strongly fell in the low-paying services profession, with the declining and middle-paying production profession being 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 employ-

[7]Notice that in 2014, production, operator, and crafts occupations still make up almost fifty percent of overall employment, whereas the other professions are much smaller (Panel (a), Appendix Figure A10).

Figure 1: Professions' Wage and Employment Trends

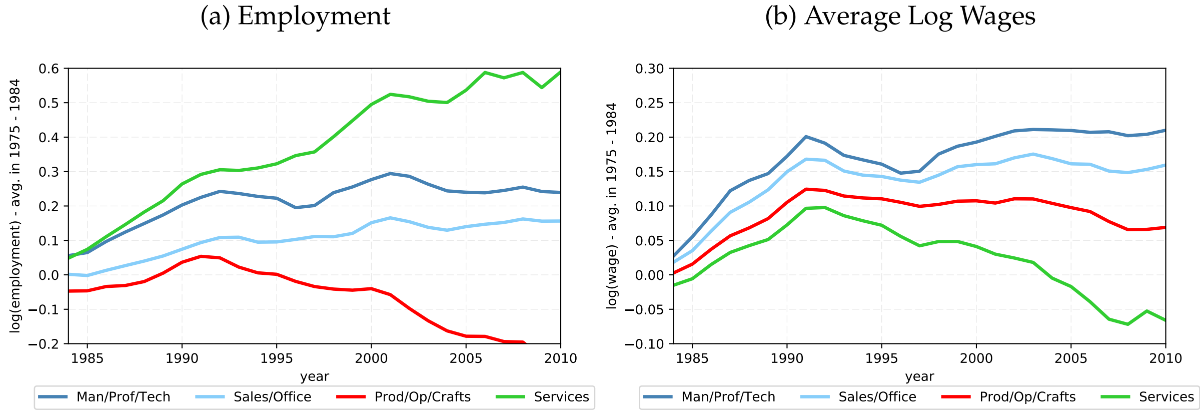


Table 1: Labor Market Entrants' by Profession and Cohort; Average Wages of Profession Entrants and Leavers Relative to Stayers

Panel A cohort	(1950, 1960]	(1960, 1970]	(1970, 1980]	(1980, 1990]
Man/Prof/Tech	0.11	0.09	0.10	0.12
Sales/Office	0.13	0.11	0.13	0.14
Prod/Op/Crafts	0.64	0.66	0.52	0.46
Services	0.05	0.06	0.08	0.08
Unemp/OLF	0.06	0.09	0.17	0.20

Panel B status	entrant	leaver	entr. or lvr	avg net entry
Man/Prof/Tech	-0.412	-0.113	-0.264	0.005
Sales/Office	-0.340	-0.125	-0.234	0.003
Prod/Op/Crafts	-0.269	-0.108	-0.183	-0.010
Services	-0.309	-0.217	-0.265	0.016

Source: SIAB data, own calculations. Panel A: the numbers show employment status at age 25. The unemployed / out of the labor force category is mainly made up of individuals not yet observed at this age in our data; the largest group here is presumably students in tertiary education (lines up well with external numbers on this). Panel B: the base category are workers who stay in the same profession from $t-1$ until $t+1$. The numbers show the relative wages in t of workers who enter the profession at the beginning of the period or leave the profession at its end. *Legend:* Man/Prof/Tech: Managers, professionals, and technicians; Sales/Off: Sales and office; Prod/Op: Production workers, operators, and craftsmen; Unemp/OLF: Unemployed or out of the labor force.

ment 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) and to a rising share of employment in non-routine analytical (Man/Prof/Techn) and interactive (Sales/Office) as well as non-routine manual (Service) professions, which we saw in Panel (a) of Figure 1.

But this should at the same time lead to wage gains in these growing professions, which we only partially find in Figure 1, Panel (b), as wages in services are falling even more than in production professions. Other potential demand shocks, for example based on trade and offshoring (e.g. Blinder and Krueger, 2013) should lead to the same predictions, while a supply shock would lead to the inverse trends with rising wages in production 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 experience 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. 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, which is shown in Table 1.The first column reports the average (log) wage differences between entrants and stayers for each of the professions. The second column provides the corresponding difference for leavers and the last column the average difference between stayers and pooled marginal workers (entrants or leavers). Though smaller, these differences and the averages are still strikingly large. Tables 4 and 6 below break up the relative wages of leavers and entrants by destination and source, including unemployment and out of the labor force.

Rising sectors tend to feature more lower-than-average-earning entrants and fewer lower-than-average-earning leavers than declining sectors, which leads to substantial net entry for the growing professions and net exit for production / crafts documented in Figure 1, Panel (b). These quantitatively large differences suggest 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.[8]

2.3 Individual Dynamics

In this section, we lay out 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 2 we graph the employment shares and average wages by sector of workers born in 1955–1965 who started in the four different professions, respectively. These different starters are systematically different in the sense that the starting profession is strongly predictive of later professions in life, especially for starters in managerial and for starters in production occupations (Panels (a) and (e)).

The differences are potentially even more striking in terms of wages. Focusing on the black lines in the respective panels, average starting wages differ not only by about 30 log points between starters in managerial and services professions, with sales and production professions in between, but also in terms of life-cycle profiles, whereby wage growth of managerial starters is much higher (60 log points gain between age 25 and 50) and of production 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 professions they work in. In fact, the history of professional choice seems to matter systematically even conditional on current professional choice, since for example sales, production, and services workers' wages (light blue, red, and green series) are much higher for starters in managerial professions (Panel (b)) than of starters in production or services professions (Panels (f) and (h)).

Our estimation model in Section 3 will capture these different systematic dynamics in workers' career profiles, but it will also address important idiosyncratic differences across individual workers within these observable groups. In particular, the left panels of Figure 2 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 sales (Panel (c)) and services (Panel (g)) professions of which both

[8]Young (2014) proposes a similar explanation in the context of structural change and examines it theoretically and in cross-sectional data.

Figure 2: Employment and Wage Dynamics for Starters in the four Professions

(a) Empl Shares (Man/Prof/Tech)

(b) Wages (Man/Prof/Tech)

(c) Empl Shares (Sales/Office)

(d) Wages (Sales/Office)

(e) Empl Shares (Prod/Op)

(f) Wages (Prod/Op)

(g) Empl Shares (Services)

(h) Wages (Services)

The eight panels plot the employment share (left) and average log wages by profession (right) of workers born in 1955–1965 who start in the respective profession at age 25 over their life cycle. The black line is the average wage over all four professions for these respective starters.

less than sixty percent work in their initial profession at age 50. This suggests that even within the same gender, age, education, location, and professional history including tasks, substantial heterogeneity in career paths exists that cannot be modeled by observable variables alone.[9]

In addition, there is also 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 managerial position (dark blue line) and strikingly lower wages when they switch to production or services roles (red and green lines) during their careers. This 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.[10]

Another fact which hints at such idiosyncratic skill shocks is the multi-directionality of workers' job choices. That is, in the left panels of Figure 2, there exist for example workers who switch from production to managerial professions as well as workers who switch from managerial to production professions. 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 move only in one direction (i.e. from production to managerial) over their careers. 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 managerial jobs (Panel (b)), while they are lower for stayers than for all starters in services jobs (Panel (h)). 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 2), but also in terms of wages (right panels), both driven by idiosyncratic skill shocks. This leads to biased results, and hence we only show such estimates in robustness checks with the appropriate cautionary notes attached.

[9]We have also constructed the panels of Figure 2 conditioning on the same level of education (e.g. apprenticeship), county of residence, and measured task intensities; and found similar results.

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

Table 2: Percentages of Switchers and Stayers across categories

t t - 2	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	19.17	0.46	0.25	0.07
Sales/Office	0.53	10.60	0.28	0.07
Prod/Op/Crafts	0.64	0.43	44.67	0.52
Services	0.09	0.09	0.44	4.82
unem	0.33	0.26	1.32	0.35
olf	0.98	0.46	0.92	0.36

Table 3: Percentages of Switchers, conditional on State in $t-2$

t t - 2	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	92.47	2.23	1.21	0.33
Sales/Office	4.38	87.60	2.35	0.58
Prod/Op/Crafts	1.31	0.88	91.15	1.07
Services	1.48	1.42	7.27	79.64
unem	5.77	4.60	22.97	6.03
olf	15.46	7.21	14.51	5.68

Table 4: Wages of Switchers, before switching

t t - 2	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services	unem	olf
Mana/Prof/Tech	57139.0	51303.0	39107.1	37181.4	44555.5	46640.9
Sales/Office	50058.7	44711.9	30822.2	29033.6	34495.4	32786.9
Prod/Op/Crafts	38990.8	32699.1	34592.0	27963.6	27688.2	27108.7
Services	34840.9	28733.6	26280.7	32978.6	22864.3	21889.5

Table 5: Percentages of Switchers, conditional on State in t

t t - 2	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	88.17	3.76	0.53	1.11
Sales/Office	2.44	86.16	0.59	1.14
Prod/Op/Crafts	2.95	3.52	93.28	8.46
Services	0.41	0.70	0.92	77.88
unem	1.53	2.15	2.76	5.60
olf	4.50	3.71	1.92	5.81

Table 6: Wages of Switchers, after switching

t t - 2	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	59989.4	54537.2	39747.1	38241.8
Sales/Office	54919.4	46851.8	32090.4	29325.9
Prod/Op/Crafts	42547.3	34273.2	35290.3	27657.5
Services	39346.2	31428.8	28435.6	33794.3
unem	38947.2	30578.5	26307.6	21924.2
olf	44663.3	33759.4	26601.0	23319.7

3 A Multisector Roy Model for Estimating Task Prices

In order to account for the stylized facts, we need a model that allows for endogenous switching because of heterogeneous skill accumulation profiles. Part of switching is driven largely by career profiles rather than task prices, e.g. rise in M/P/T between 30 and 40 mirrored by corresponding drop in Op/Crafts, regardless of cohort. The entire literature is essentially doing a decomposition of wages into skills and prices. By following individuals across jobs, we can be particularly general in the skill dimension over the life cycle.

Advantages of our approach are that it is easy to implement and that there is maximum transparency which moments are used for identification. In contrast to fully structural methods, we can easily allow for multiple sectors. First-differencing performs a similar function as fixed effects, i.e. flexibly removing all individual-specific time-invariant differences.

3.1 General Setup

There are $k = 1, \ldots, K$ distinct professions. Each worker is endowed with a vector of sector specific, idiosyncratic skills $S_{i,t} = \begin{pmatrix} S_{1,i,t} & S_{2,i,t} & \ldots & S_{K,i,t} \end{pmatrix}$. A worker's potential wages obtain as the product of profession-specific prices paid for a unit of skilled labor, $\Pi_{k,t}$, and his skills in profession k. The main objective of this paper is to estimate the evolution of $\Pi_{k,t}$ over the past thirty years. Letting lowercase characters denote the logarithm of a variable, we thus obtain:

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

A worker chooses to work in the profession in which he earns the highest wage:

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

By the envelope theorem, a marginal change in the potential wage at time t then is:

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

where $I_{k,i,t} = \mathbb{1}[\max_{j=1,\ldots,K}\{w_{j,i,t}\} = w_{k,i,t}] = \mathbb{1}[w_{k,i,t} \geq w_{j,i,t}\ \forall j \neq k]$ is the profession choice indicator. We can rewrite this to:

$$dw_{i,t} = I_{1,i,t}dw_{1,i,t} + \ldots + I_{K,i,t}dw_{K,i,t} = \sum_{k=1}^{K} I_{k,i,t}dw_{k,i,t} \tag{3}$$

Equation (3) states that a worker's observed wage changes by the same amount as the potential wage in his chosen profession in the case of marginal changes. Since we are interested in discrete changes of (potential) wages, we need to take the wage effect from an endogenous change of the chosen profession into account. In particular, we integrate over Equation (3) from $t-1$ to t (details of the derivation in Appendix Section A):

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

where Δ denotes the change between the points in time t and $t-1$. This result is quite intuitive: if a worker stays in his occupation k between the two points in time ($I_{k,i,t} = I_{k,i,t-1} = 1$), his observed wage change is equal 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 k to some other profession k', he obtains part of the initial profession's wage gain as well as part of the final profession's wage gain with the relative size of these parts determined by the point of indifference. This is also intuitive, as the worker has comparative advantage both in his initial and in his final profession.

While Equation (4) is directly observable for profession stayers, we need to approximate it for switchers in order to use it for empirical analyses. In particular, we linearly interpolate the choice indicator for $\tau \in (t-1, t)$ as we only observe workers in the endpoints of two periods t and $t-1$ but not in between when the prices become so that workers are indifferent between the choice of two professions:

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

We show in Appendix Section C that the approximation is immaterial for our results. After plugging this approximation into (4), we end up with a very intuitive result (details of the derivation in Appendix Section A):

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta w_{k,i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta \pi_{k,t} + \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta s_{k,i,t}, \tag{6}$$

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.

Due to the approximation of the integral, the wage change for i from $t-1$ to t can be decomposed as follows: If i stays in profession k, he gets a potential wage gain $\Delta w_{k,i,t}$ from that profession. If i switches, he gets half of the potential wage gain from the origin and half from the destination profession.[11] If we didn't approximate the integral, the decomposition would be more exact. For example, the worker could receive 1/8 of the wage gain of his previous profession and 7/8 of the gain of his destination profession. However, since the estimation computes expectations over all workers who make a particular switch, the difference between our assumption and average gain in the origin and the destination profession tends to be very small (the Monte Carlo Simulations in Appendix Section C.1 confirm this).

To estimate (6), we need data on log wage changes $\Delta w_{i,t}$, profession choices from which we construct $\bar{I}_{k,i,t}$, and the changes in skills. As we don't have direct measures of skill changes $\Delta s_{k,i,t}$, we estimate them in the data together with the task prices $\Delta \pi_{k,t}$.

3.2 Accounting for Heterogeneous Career Profiles

Allowing for the life-cycle employment and wage profiles documented in Figure 2 requires a fairly general model of skill accumulation. We do so by employing a flexible control variable specification. We also show how we employ a pre-period in order to

[11] For example, if the worker switched from k to j, his observed wage gain would be decomposed into:

$$\Delta w_{i,t} = \frac{1}{2} \underbrace{\Delta(\pi_{k,t} + s_{k,i,t})}_{\Delta w_{k,i,t}} + \frac{1}{2} \underbrace{\Delta(\pi_{j,t} + s_{j,i,t})}_{\Delta w_{j,i,t}}$$

disentangle skill accumulation from changing task prices in the data.

We model skill acquisition as learning by doing on the job, similar in spirit to Yamaguchi (2012). In particular, workers accumulate skills by performing bundles of tasks in their profession last period, which may yield different profession-specific increases in productivity in the current period:

$$\Delta s_{k,i,t} = \sum_{k'=1}^{K} \sum_{a=1}^{A} I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a] \cdot \gamma_{k,k',a} + v_{i,t}, \tag{7}$$

where $\gamma_{k,k',a}$ is an element of the skill-accumulation transition matrix which maps previous period's job k' experience into productivity increases for job k. We have made this specification age-dependent, since actual life-cycle wage growth depends on age. In the empirical analysis we additionally show results where the specification is education-dependent as well, and we include direct measures of analytical, interactive, routine, and manual tasks into Equation (7) on top of the profession dummies $I_{k',i,t-1}$. The term $\sum_{k'=1}^{K} \sum_{a=1}^{A} \gamma_{k,k',a} \cdot I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a]$ therefore flexibly captures average wage growth of individuals of different ages who choose all combinations of professions in the previous and current period. However, workers also experience idiosyncratic wage changes *within* these groups, which may be due to faster or slower learning on the job than average. This is captured by the idiosyncratic term $v_{i,t} \sim iid(0, \sigma_v^2)$, which for now does not carry a k index and therefore does not influence workers' choices. In the next sub-section, we present the case when $v_{i,t}$ is profession-specific.

Inserting the skill accumulation specification into Equation (6) yields our baseline model of workers' wage growth between periods $t-1$ and t:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta \pi_{k,t} + \sum_{k=1}^{K} \sum_{k'=1}^{K} \sum_{a=1}^{A} \bar{I}_{k,i,t} I_{k',i,t-1} \cdot \mathbb{1}[\text{age}_{i,t-1} \in a] \cdot \gamma_{k,k',a} + u_{i,t}, \tag{8}$$

with the error term $u_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t} v_{i,t} = v_{i,t}$. As Equation (8) stands, the regressors $\bar{I}_{k,i,t}$ for changes in task prices and the skill accumulation parameters are collinear. In order to disentangle $\Delta \pi_{k,t}$ from $\gamma_{k,k',a}$, we therefore introduce a pre-period (from $t = 0$ to $t = 1$) in which we assume that task prices do not change. This allows us to identify $\gamma_{k,k',a}$ for all k, k', a in the pre-period. More generally, since we are not interested in absolute task prices or skills in our analysis, but in relative values of these variables across professions ($\tilde{s}_{k,i,t} \equiv s_{k,i,t} - s_{1,i,t}$ and $\tilde{\pi}_{k,t} \equiv \pi_{k,t} - \pi_{1,t}$ where 1 indexes a reference profession), the weaker assumption that relative task prices are constant (i.e. $\Delta \tilde{\pi}_{k,1} = 0$ for all k) in the pre-period will be sufficient for our empirical analysis.

To illustrate this argument in a simplified example, consider Equation (8) with two professions, without age-dependence, and expressed relative to the reference profession:[12]

$$\Delta w_{i,t} = \Delta\pi_{1,t} + \bar{I}_{2,i,t}\Delta\tilde{\pi}_{2,t} + [\gamma_{1,1} + I_{2,i,t-1}(\gamma_{1,2} - \gamma_{1,1})] +$$

$$+ [\bar{I}_{2,i,t}\tilde{\gamma}_{2,1} + \bar{I}_{2,i,t}I_{2,i,t-1}(\tilde{\gamma}_{2,2} - \tilde{\gamma}_{2,1})] + u_{i,t}, \tag{9}$$

with $\tilde{\gamma}_{2,1} \equiv \gamma_{2,1} - \gamma_{1,1}$ and $\tilde{\gamma}_{2,2} \equiv \gamma_{2,2} - \gamma_{1,2}$. The first term in brackets $[\gamma_{1,1} + I_{2,i,t-1}(\gamma_{1,2} - \gamma_{1,1})] = E(\Delta s_{1,i,t}|I_{2,i,t-1}, \bar{I}_{2,i,t})$ is the expected skill accumulation in the reference profession, while the second term $[\bar{I}_{2,i,t}\tilde{\gamma}_{2,1} + \bar{I}_{2,i,t}I_{2,i,t-1}(\tilde{\gamma}_{2,2} - \tilde{\gamma}_{2,1})] = E(\Delta\tilde{s}_{2,i,t}|I_{2,i,t-1}, \bar{I}_{2,i,t})$ is the expected relative skill accumulation in profession 2. If $\Delta\tilde{\pi}_{2,1} = 0$, we can identify the relative skill accumulation coefficients via regression (9) in the pre-period. Given $\tilde{\gamma}_{2,1}$ and $\tilde{\gamma}_{2,2}$, in the other periods $t > 1$, we can identify the changing relative task prices $\Delta\tilde{\pi}_{2,t}$. The relative strength of skill accumulation in the reference profession $(\gamma_{1,2} - \gamma_{1,1})$ from working in profession 2 is also identified, so that only identification of the intercept $\gamma_{1,1}$ would require the stricter assumption of $\Delta\pi_{1,1} = \Delta\pi_{2,1} = 0$.

We provide empirical support for the assumption $\Delta\tilde{\pi}_{k,1} = 0, \forall k$ in our chosen pre-period 1975–1985 in Section 4 and we show robustness by estimating the model with different choices of pre-period in Section 5. However, notice that even if (relative) task prices were not constant in the pre-period, the estimates from Equation (8) would identify accelerations or decelerations of (relative) task price growth compared to the pre-period (i.e. $\widehat{\Delta\tilde{\pi}}_{k,t} = \Delta\tilde{\pi}_{k,t} - \Delta\tilde{\pi}_{k,1}$). This is still an important parameter for understanding the dynamics presented in Section 2, because it summarizes how wage growth of workers in different professions (and thus their relative attractiveness) has accelerated or decelerated over time.[13]

Section C.1 provides Monte Carlo evidence that regression (8) identifies the correct *relative* task prices as well as the correct *relative* skill accumulation parameters under the assumptions laid out above.

[12]The intermediate step is $\Delta w_{i,t} = \Delta\pi_{1,t} + \bar{I}_{2,i,t}\Delta\tilde{\pi}_{2,t} + (1 - \bar{I}_{2,i,t})(1 - I_{2,i,t-1})\gamma_{1,1} + \bar{I}_{2,i,t}(1 - I_{2,i,t-1})\gamma_{2,1} + (1 - \bar{I}_{2,i,t})I_{2,i,t-1}\gamma_{1,2} + \bar{I}_{2,i,t}I_{2,i,t-1}\gamma_{2,2} + u_{i,t}$.

[13]In our simplified example, if $\Delta\tilde{\pi}_{2,1} \neq 0$ the estimates of relative skill accumulation from the pre-period become $[\bar{I}_{2,i,t}\hat{\tilde{\gamma}}_{2,1} + \bar{I}_{2,i,t}I_{2,i,t-1}(\hat{\tilde{\gamma}}_{2,2} - \hat{\tilde{\gamma}}_{2,1})] = E(\Delta\tilde{s}_{2,i,t}|I_{2,i,t-1}, \bar{I}_{2,i,t}) + \Delta\tilde{\pi}_{2,1}$. Accordingly, in all other periods $t > 1$, $\widehat{\Delta\tilde{\pi}}_{2,t} = \Delta\tilde{\pi}_{2,t} - \Delta\tilde{\pi}_{2,1}$ gives the accumulation or deceleration of *relative* task price growth *relative* to the pre-period.

3.3 Including Differential Idiosyncratic Skill Changes

In this section, we present our most general model by allowing skill accumulation to be idiosyncratic by individual and differential across professions. This is strongly suggested by the facts summarized in Figure 2 and it generates a potential endogeneity concern. However, we show that our baseline method is largely robust to this (it does change the interpretation of the skill accumulation parameters, however). We also present an alternative instrumental (IV) variables strategy to address the endogeneity concern.

Suppose workers have different idiosyncratic skill shocks for each profession in addition to the systematic accumulation presented in Section 3.2. The error term in Equation (8) becomes $u_{i,t} \equiv \sum_{k=1}^{K} \bar{I}_{k,i,t} v_{k,i,t}$, where $v_{k,i,t}$ is an innovation with respect to the previous period in the sense that its expectation conditional on all predetermined variables is zero (e.g. $E(v_{k,i,t}|I_{k',i,t-1} = 0)$ for all k'). Other than that we allow for any joint distribution function $F(v_{1,i,t}, ..., v_{K,i,t})$ of $v_{k,i,t}$s so that, for example, idiosyncratic skill updates can be correlated among similar professions in an unrestricted way.

The differential idiosyncratic skill shocks introduce an endogeneity bias into regression (8), because these changes affect current period task choices in $\bar{I}_{k,i,t}$. To see this bias most clearly, return to our simplified example (9) ignoring systematic skill accumulation for now:

$$\Delta w_{i,t} = \Delta\pi_{1,t} + \bar{I}_{2,i,t}\Delta\tilde{\pi}_{2,t} + v_{1,i,t} + \bar{I}_{2,i,t}\tilde{v}_{2,i,t}, \tag{10}$$

with $\tilde{v}_{2,i,t} \equiv v_{2,i,t} - v_{1,i,t}$ the *relative* idiosyncratic skill changes, which affect task choices. In particular, an OLS regression yields the following estimate for the changing relative task price

$$\widehat{\Delta\tilde{\pi}}_{2,t} = \frac{cov(\Delta w_{i,t}, \bar{I}_{2,i,t})}{Var(\bar{I}_{2,i,t})} = \Delta\tilde{\pi}_{2,t} + \frac{cov(\bar{I}_{2,i,t}\tilde{v}_{2,i,t}, \bar{I}_{2,i,t})}{Var(\bar{I}_{2,i,t})}, \tag{11}$$

with $\bar{I}_{2,i,t} = \frac{I_{2,i,t}+I_{2,i,t-1}}{2}$ and $I_{2,i,t} = \mathbb{1}[\tilde{\pi}_{2,t} + \tilde{s}_{2,i,t-1} + \tilde{v}_{2,i,t} > 0]$. Hence, there is classical endogeneity bias in the second summand on the right hand side of Equation (11), which stems from the fact that $I_{2,i,t}$ is a function of $\tilde{v}_{2,i,t}$. The induced positive correlation between these two variables should work toward a too large estimate of $\widehat{\Delta\tilde{\pi}}_{2,t}$.

One approach to remove this bias is by instrumenting the regressor $\bar{I}_{2,i,t}$ with its predetermined component $I_{2,i,t-1}$, which is not a function of $\tilde{v}_{2,i,t}$. What remains of the covariance in the numerator is then $\frac{\hat{\rho}}{2}cov((I_{2,i,t} + I_{2,i,t-1})\tilde{v}_{2,i,t}, I_{2,i,t-1})$, where $\hat{\rho}$ is the coefficient from the IV first stage ($\hat{\bar{I}}_{2,i,t} = \hat{\rho}I_{2,i,t-1}$). The second part of this covariance

$cov(I_{2,i,t-1}\tilde{v}_{2,i,t}, I_{2,i,t-1})$ is clearly zero. The first part

$$cov(I_{2,i,t}\tilde{v}_{2,i,t}, I_{2,i,t-1}) = E[I_{2,i,t-1}E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t-1})] - E(I_{2,i,t}\tilde{v}_{2,i,t})E(I_{2,i,t-1}), \qquad (12)$$

however, is indeterminate as $E(I_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t-1})$ may vary with $I_{2,i,t-1}$ in general.

The other approach to remove the bias is to control for all combinations of profession choices $I_{k,i,t-1}$ and $I_{k,i,t}$, which we in fact already do in our baseline specification with skill accumulation (8). It is easiest to see in example (9) as a fully saturated regression on all combinations of profession choices. One can therefore think of this approach as identifying the conditional expectations function $E(\Delta w_{i,1}|I_{2,i,1}, I_{2,i,0}) = \Delta\pi_{1,1} + E(\bar{I}_{2,i,1}\tilde{v}_{2,1}|I_{2,i,1}, I_{2,i,0})$ from the fully interacted pre-period (i.e. $\Delta\tilde{\pi}_{2,1} = 0$) regression and then entering it into all post-period ($t > 1$) estimations of (10):

$$\Delta w_{i,t} = \Delta\pi_{1,t} + \Delta\pi_{1,1} + \bar{I}_{2,i,t}\Delta\tilde{\pi}_{2,t} + E(\bar{I}_{2,i,1}\tilde{v}_{2,1}|I_{2,i,t}, I_{2,i,t-1}) + error_{i,t}, \qquad (13)$$

with $error_{i,t} \equiv v_{1,i,t} - \Delta\pi_{1,1} + [\bar{I}_{2,i,t}\tilde{v}_{2,i,t} - E(\bar{I}_{2,i,1}\tilde{v}_{2,1}|I_{2,i,t}, I_{2,i,t-1})]$. The expectation of $[\bar{I}_{2,i,t}\tilde{v}_{2,i,t} - E(\bar{I}_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1})]$ conditional on any combination of $I_{2,i,t-1}$ and $I_{2,i,t}$ is zero by construction.[14] Therefore, if $E(\bar{I}_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1})]$ remains reasonably close to its value in the pre-period, the $error_{i,t}$ in regression (13) is (if at all) only weakly correlated with the regressor $\bar{I}_{2,i,t}$ and the correct changes in relative task prices $\Delta\tilde{\pi}_{2,t}$ are identified.

We employ both the baseline model (8) and instrumental variables in the empirical analysis. In Appendix Sections A.3 and A.4 we argue analytically that in both cases the estimates $\widehat{\Delta\tilde{\pi}}_{2,t}$ should to be moderately downward biased in absolute value. The Monte Carlo Simulations in Section C.2 confirm that the bias is small under plausible parameter values, and that the baseline and IV approaches each provide a lower bound for the true size of the relative task price changes. What holds true for both approaches is that the more of workers' skill accumulation can be captured systematically (i.e. via the variables in Equation (7)), the less variation in $\tilde{v}_{k,i,t}$ and the smaller the bias (i.e. $\frac{cov(\bar{I}_{2,i,t}\tilde{v}_{2,i,t}, \bar{I}_{2,i,t})}{Var(\bar{I}_{2,i,t})}$ in example (11)).

Finally, notice that in both the instrumental variable and the kitchen-sink approach, the estimated control variable coefficients in Equation (8) are not the structural skill accumulation parameters $\gamma_{k,k',a}$ anymore. To see this, consider the simplified example with skill accumulation (9). If $\bar{I}_{2,i,t}$ is instrumented by $I_{2,i,t-1}$, only one coefficient $\hat{\gamma}_1$ for

[14] That is, returning to the covariance term in expression (11), $cov([\bar{I}_{2,i,t}\tilde{v}_{2,i,t} - E(\bar{I}_{2,i,t}\tilde{v}_{2,i,t}|I_{2,i,t}, I_{2,i,t-1})], \bar{I}_{2,i,t}) = 0$.

workers with $k = 1$ in $t-1$ and one coefficient $\hat{\gamma}_2$ for workers with $k = 2$ in $t-1$ can be identified. These coefficients provide the average relative wage growth due to skill accumulation (including due to switching) of initially working in profession 1 and 2, respectively. In the baseline model, $\frac{1}{2}(\hat{\gamma}_{2,1}-\hat{\gamma}_{1,1})$, $\frac{1}{2}(\hat{\gamma}_{1,2}+\hat{\gamma}_{2,2}-\hat{\gamma}_{2,1}-\hat{\gamma}_{1,1})$, and $\hat{\gamma}_{2,2}-\hat{\gamma}_{1,1}$ are the average skill accumulation (including idiosyncratic shocks) of switchers from $k = 1$ to $k = 2$, from $k = 2$ to $k = 1$, and of stayers in $k = 2$, respectively, relative to stayers in profession 1. Since, these combined coefficients are the richer set of parameters (and the structural parameters without idiosyncratic skills shocks), the baseline model is our main specification in the paper.

4 Empirical Results

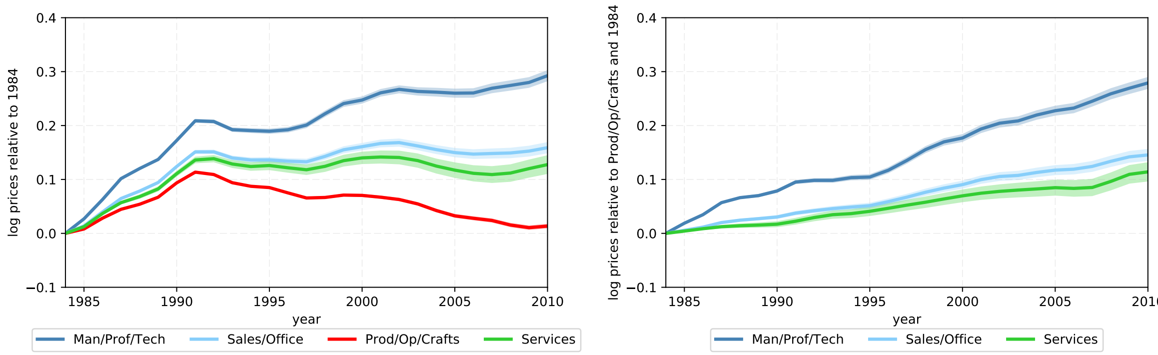
4.1 Estimated Task Prices and Accumulation Coefficients

Figure fig:prices-a shows the accumulated price changes over time $\pi_{k,t} = \sum_{\tau=1985}^{t} \Delta\pi_{k,\tau}$ normalized to zero in 1984. There are several interesting facts to mention. First, task price changes were positive across the board in the second half of the 1980s until 1990 with an increase between 9 log points for Production/Operators/Craftsmen and 17 log points for Managers/Professionals/Technicians corresponding to roughly 9% and 19%, respectively. This is in line with almost equally fast real log wage growth in that period. Second, after the reunification, the picture becomes more diversified as only the prices of Managers/Professionals/Technicians increased further up to 29 log points ($\approx 34\%$). In contrast, the price for work in the producing sector declined by 8 log points after 1990. The returns to service and office work stagnated from 1990 onwards or increased only slightly.

Third, and probably most striking, is the fact that the task price for services accelerated relative to production, operators, and craftsmen as seen in the right panel 3 where the price of production, operators, and craftsmen was deducted from all other prices. Between 1985 and 2010, the relative price for managerial, professional technical work rose by 28 log points more than that of producing work whereas the relative price for clerical and service work increased by 14 and 12 log points, respectively.

This is exactly contrary to differences in mean wages between services and production, operators, and craftsmen for both men and women. Through the lens of the model, this implies that the response towards increasing service prices led to a large deterioration of the average service skill. This result is also found in other studies esti-

Figure 3: Estimated task prices



Source: SIAB data, own calculations. The upper panel shows the estimated accumulated task price changes over time normalized to zero in 1984. The lines in the lower panel were computed by additionally subtracting the accumulated 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 price estimates were received using the main sample of full-time male workers, aged 25 - 54, dropping foreigners as well as spells from East Germany. *Legend:* Man/Prof/Tech: managers, professionals, and technicians; Sales/Off: sales and office; Prod/Op/Crafts: production, operators, and craftsmen.

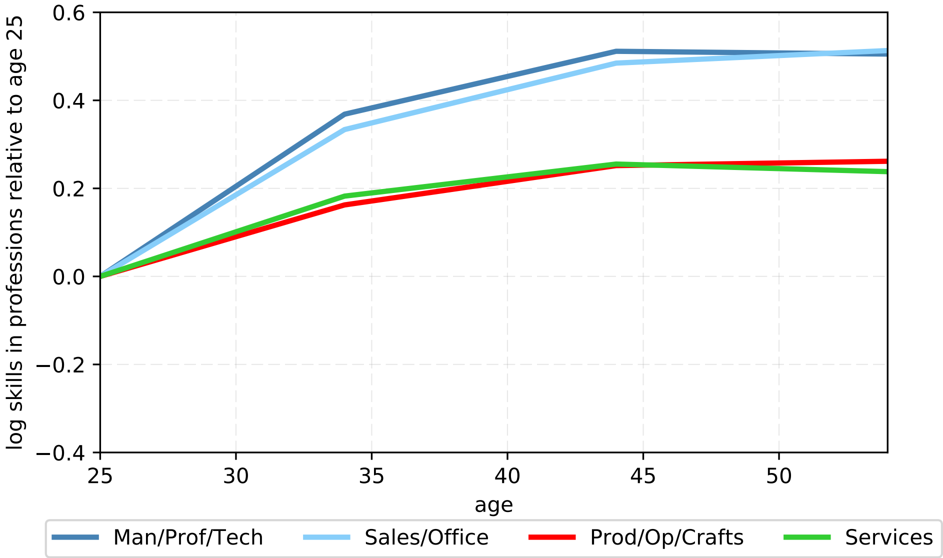
mating task prices either for the US (Cortes, 2016; Gottschalk et al., 2015; Böhm, 2017), the UK (Cavaglia and Etheridge, 2017) or Germany (Cavaglia and Etheridge, 2017). The finding is consistent with a substantial impact of routine biased technical change proposing that the reduction in the price of computer capital led to a decrease in the relative demand for producing tasks as those can be substituted most easily (Autor et al., 2003; Acemoglu and Autor, 2011). However, it is also consistent with increased competition for producing workers from abroad through intensified offshoring possibilities (Goos et al., 2014).

What happens to task price estimates if one ignores life cycle skill accumulation? Despite the fact that the order of the price changes is unaffected, there is a substantial difference in magnitude of the absolute estimates. This would not be a problem for the *relative* estimates if life cycle skill accumulation was the same for all professions. However, the data reject this hypothesis as 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 managers, professionals, and technicians as well as sales and office differ largely to the estimates obtained from including skill accumulation controls. The relative service prices, however, are similar to ones including skill accumulation which suggests that the skill growth profiles of producing and service occupations are similar.

Another problem that reinforces 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 would have led to an increase in average wages because of more average skill accumulation. Thus, ignoring skill accumulation leads to an overestimation of price changes[15]. The converse argument holds if old workers' skills depreciate and entering, i.e. young, cohort become smaller over time making the work force age.

Figure 4 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 $\gamma_{k,k,a}$ over the respective ages. The emerging pattern is that skill accumulation is strongly concave over the life cycle, i.e. $\gamma_{k,k,a} > \gamma_{k,k,a'}$ for $a < a'$[16]. The accumulation is strongest for managers, professional, and technicians as well as sales and office workers with an increase of 54% log points between ages 25 and 54. The surge is less pronounced for production workers (30 log points) and smallest for services (20 log points) with indication of skill depreciation after age 44 for services.

Figure 4: Estimated skill accumulation



Source: SIAB data, own calculations. The figure 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 same sample of men, aged 25-54 was used as for the price estimates. The results are presented in accumulated form $\sum_{\text{age} \in a} \hat{\gamma}_{k,k,a}$ over the ages in the life cycle.

Legend: Man/Prof/Tech: managers, professionals, and technicians; Sales/Off: sales and office; Prod/Op/Crafts: production, operators, and craftsmen.

[15]For instance, applying the method of Cortes (2016), which ignores skill accumulation to a large extent, to our sample leads to almost identical results without any controls for skill accumulation.

[16]Notice that, because skills in our model are completely distinct categories, a hierarchical ranking, as for instance in Cortes (2016), between the skills is not possible and so only a comparison of skills within profession between ages is meaningful. Simply speaking, the skills of a craftsmen are completely distinct from the skills of a manager making it not possible to compare them.

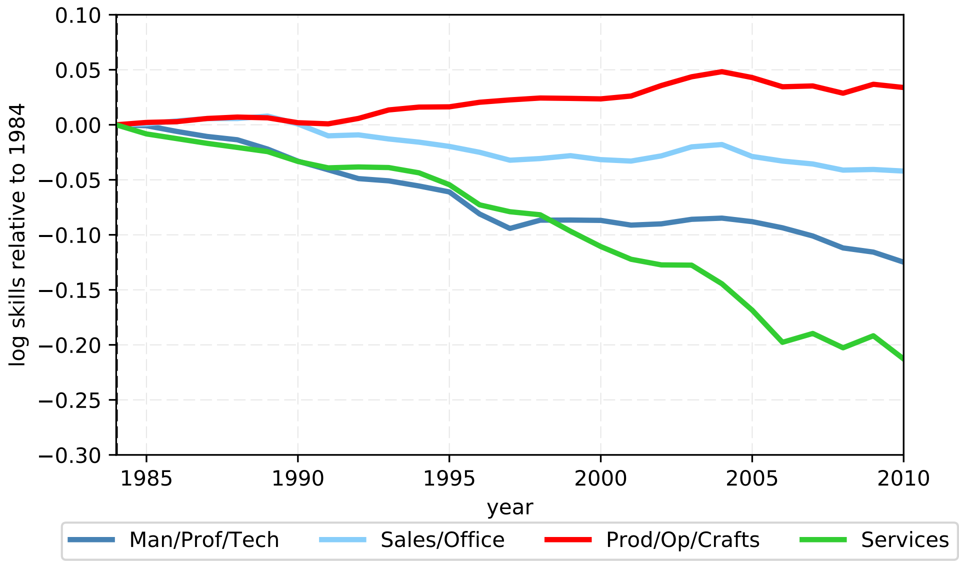
4.2 Analysis of Skill Selection into Professions

This section analyses the selection of skills into professions implied by the task prices. We conduct a decomposition showing that the negative selection effect into growing professions relative to production and crafts is almost entirely due to the net entry on the margin of less skilled workers. Moreover, a substantial part of these differences stem from skill accumulation of stayers relative to profession entrants or leavers.

Figure 5 graphs the mean skill change over time for each profession:[17]

$$\underbrace{\mathrm{E}[w_{i,t}|I_{k,i,t}=1]-\mathrm{E}[w_{i,t-1}|I_{k,i,t-1}=1]}_{\text{mean wage change}}=\underbrace{\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1]}_{\text{mean skill change}}+\underbrace{\Delta\pi_{k,t}}_{\text{price change}} \tag{14}$$

Figure 5: Implied skill selection



Source: SIAB data, own calculations. 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: Man/Prof/Tech: managers, professionals, and technicians; Sales/Off: sales and office; Prod/Op/Crafts: production, operators, and craftsmen.

This skill change is "implied" because we calculate it as the difference between the observed change in the average wage and the estimated task prices. The results show 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

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

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.[18] It is also reflected in the lower wages of entering and leaving workers compared to incumbents or stayers reported in Table 1 above. Therefore, skills in rising sectors may become more negatively selected *because of* their growth and vice versa for skills in declining sectors.

To further investigate this possibility, it is most informative to plot the three components of (14) 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 6, with the absolute levels for production and crafts and relative for the three other professions. We indeed see in Figure 6 that for all three professions with rising (relative) task prices skill selection is negative and pulling down average wages. This is substantially attenuating average wages for managerial and sales professions and even overturning the effect of the task prices in the case of the low-earning services profession.

Such strong selection effects 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 (14) into three components:[19]

$$\begin{aligned}
\mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = \; & \underbrace{\left(1-h^{lvr}_{k,t-1}\right)\cdot \mathrm{E}[\Delta s^{sty}_{k,i,t}]}_{\text{1 \textbf{learn}ing: accumulation of stayers}} \\
& + \underbrace{h^{lvr}_{k,t-1}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\text{2 \textbf{churn}ing: difference entrants, leavers}} \\
& + \underbrace{\left(h^{ent}_{k,t}-h^{lvr}_{k,t-1}\right)\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{sty}_{k,i,t}]\right)}_{\text{3 \textbf{marg}inal \textbf{sel}ection}}
\end{aligned} \tag{15}$$

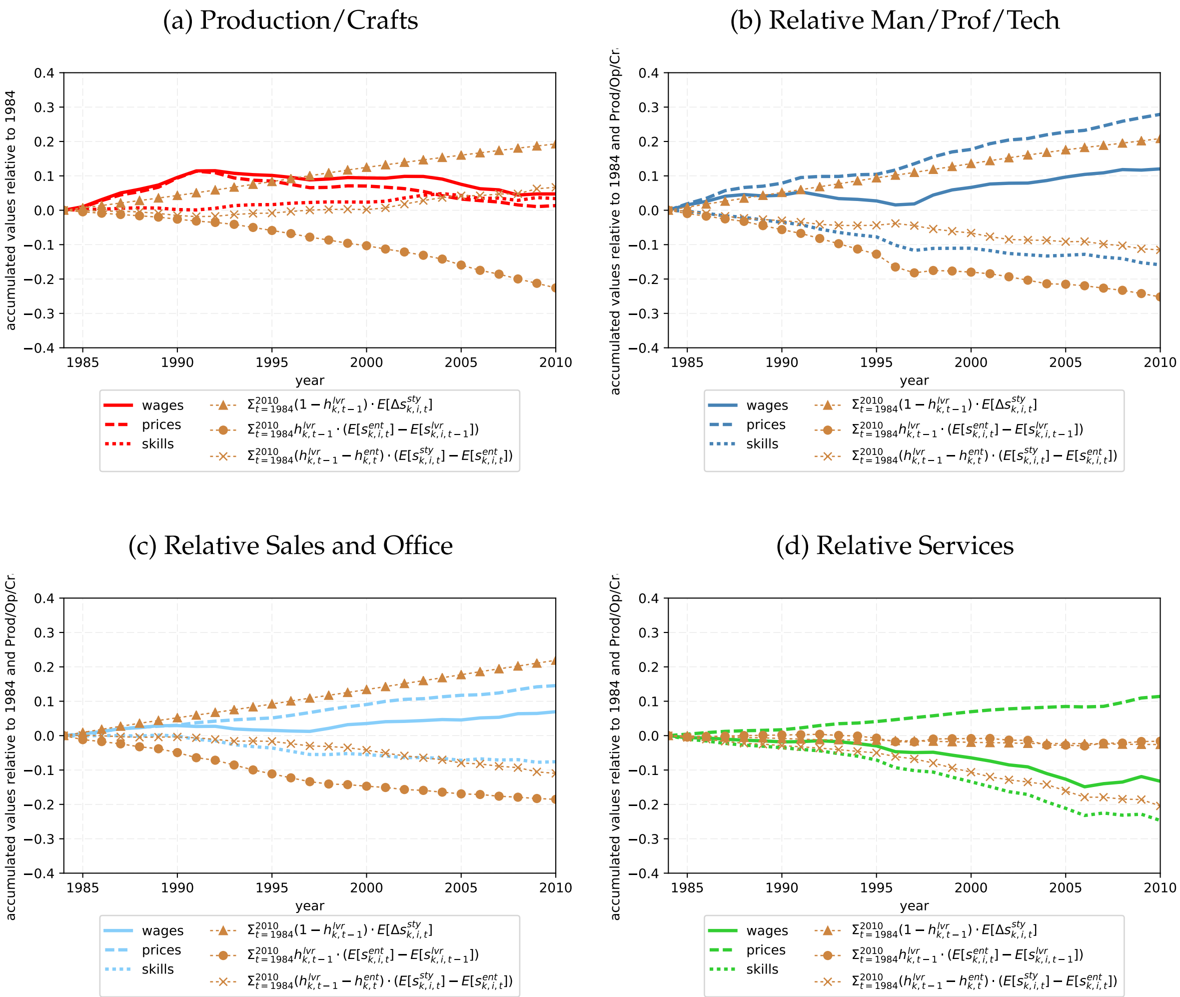
Here, superscript sty indicates a profession stayer, lvr a leaver, and ent an entrant. $h^{lvr}_{k,t-1}$ indicates the share of last period's workers in k who left the profession in this

[18]Young (2014) shows formally that this result requires that workers' skill differences need to largely be based on comparative as opposed to absolute advantage .

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

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

Figure 6: Average Wages, Task Prices, and Implied Skills in Professions. Decomposition of Skills into Accumulation, Churning, and Marginal Selection



Notes: The colored main series in the top left panel of the Figure 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* production and crafts. The brown dashed and dotted series show Equation (15)'s further decomposition of professions' skill selection into effects due to accumulation, churning, and marginal selection. Find the absolute values of all professions in appendix figure A12.

period and $h^{ent}_{k,t}$ the share of this period's workers who entered this period.[20] An alternative decomposition based on the marginal selection of leavers and the corresponding figures are in Appendix D.1.

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 managerial and sales professions according to our estimates, this raises the first term in Equation (15). 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 and the deteriorating impact of churning (second term of (15)) 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. Strikingly, we see in all four panels of Figure 6 that the golden lines with triangle and dot markers indeed approximately sum to zero.

Therefore, the changes in sectors' skill composition must largely be due to the third term of Equation (15), 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 positive for all professions according to relative wages reported in Table 1 above, while net entry is positive for growing and negative for shrinking sectors. We see in Figure 6 that this marginal selection effect almost perfectly coincides with the overall change in the skill composition of the services profession and it is even slightly stronger in absolute value than the overall change in the skill composition of the other three sectors.

Notice that the marginal selection effect does not depend on the 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 close overlap with the implied skill selection therefore provides independent evidence supporting the correctness of our estimates. In addition, the marginal

[20] Formally, the components are defined as

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

selection effect 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 important result. The alternative decomposition to Equation (15) in Appendix D.1 based on the marginal selection of leavers instead of entrants is slightly weaker in absolute value than the overall change in the skill composition of the four sectors. Therefore, an "average decomposition"[21] would come to the conclusion that the marginal selection effect fully explains the changing skill composition of the managerial, sales, and production professions and most of the changing skill composition of services. The remainder of the deteriorating skill composition of services can be inferred from Appendix Figure A13, which shows that turnover in the sector $h^{lvr}_{k,t-1}$ (or $h^{ent}_{k,t}$) has modestly but continuously increased over the sample period.[22] This leads to more negative accumulation and churning effects in Figure A6, Panel D.

The next step investigates the sources of the marginal selection effect in order to understand its economic mechanism but also as further plausibility and robustness checks.

21

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

22 Appendix Figure A13 plots the elements of the decomposition (15) in each period separately. We see that:

- Skill accumulation $\mathrm{E}[\Delta s^{sty}_{k,i,t}]$ ("skill change stayers" in the Figure legend) constant over time.
- Diff. btw entrants and leavers $\mathrm{E}[s^{ent}_{k,i,t}] - \mathrm{E}[s^{lvr}_{k,i,t-1}]$ constant.
- Turnover ("prob. of leaving") $h^{lvr}_{k,t-1}$ rises a bit for Services.
- Sector growth ("prob. of leaving - prob. of entering") $h^{lvr}_{k,t-1} - h^{ent}_{k,t}$ largely constant, but mostly negative for Man/Prof/Tech, Sales and Office, and Services while often positive for production and crafts.
- Quality of marginal selection $\mathrm{E}[s^{sty}_{k,i,t}] - \mathrm{E}[s^{ent}_{k,i,t}]$ just negative! (& increasing in all sectors). This leads to effect 3 in decomposition (15) above.

Figure XX focuses on the marginal selection effect, which we found largely drives sectors' changing skill selection (Figure 6). 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

$$\mathrm{E}[s_{k,i,t}^{ent}] = h_{k,t}^{ent,swt}\mathrm{E}[s_{k,i,t}^{ent,swt}] + h_{k,t}^{ent,UO}\mathrm{E}[s_{k,i,t}^{ent,UO}] + h_{k,t}^{ent,new}\mathrm{E}[s_{k,i,t}^{ent,new}],$$

where the shares of entrants who are profession switchers $h_{k,t}^{ent,swt}$, entering from unemployment or out of the labor force during their careers $h_{k,t}^{ent,UO}$, and new labor market entrants $h_{k,t}^{ent,new}$ sum to one. Then we plot the contributions of these groups to the marginal selection effect for each profession in the left panels of Figure XX.[23]

Second, we examine to what extent the differences in skills between incumbents and entrants reflect time-invariant endowments versus skill accumulation. We compute the skills that incumbents accumulated since they joined the sector $x_{i,t}$ periods ago in two different ways, using the estimated systematic accumulation ($s_{k,i,t}^{sty} - s_{k,i,t-x_{i,t}}^{sty} = \sum_{\tau=1}^{x_{i,t}} \sum_{a=1}^{A} I_{k,i,t-\tau} \cdot \mathbb{1}[\text{age}_{i,t-\tau} \in a] \cdot \hat{\gamma}_{k,k,a}$) and from the growth in their observed wages including idiosyncratic shocks ($s_{k,i,t}^{sty} - s_{k,i,t-x_{i,t}}^{sty} = w_{k,i,t} - w_{k,i,t-x_{i,t}} + \hat{\pi}_{k,t} - \hat{\pi}_{k,t-x_{i,t}}$). We then plot the marginal selection component from Equation (15) that is due to differences at entry $\left(h_{k,t-1}^{lvr} - h_{k,t}^{ent}\right)\left(\mathrm{E}[s_{k,i,t-x_{i,t}}^{sty}] - \mathrm{E}[s_{k,i,t}^{ent}]\right)$ versus the differences that are due to skill accumulation $\left(h_{k,t-1}^{lvr} - h_{k,t}^{ent}\right)\left(\mathrm{E}[s_{k,i,t}^{sty} - s_{k,i,t-x_{i,t}}^{sty}]\right)$ for each profession in the respective right panels of Figure XX.

[23] Formally, these contributions are $\left(h_{k,t-1}^{lvr} - h_{k,t}^{ent}\right) h_{k,t}^{ent,swt} \left(\mathrm{E}[s_{k,i,t}^{sty}] - \mathrm{E}[s_{k,i,t}^{ent,swt}]\right)$, $\left(h_{k,t-1}^{lvr} - h_{k,t}^{ent}\right) h_{k,t}^{ent,UO} \left(\mathrm{E}[s_{k,i,t}^{sty}] - \mathrm{E}[s_{k,i,t}^{ent,UO}]\right)$, and $\left(h_{k,t-1}^{lvr} - h_{k,t}^{ent}\right) h_{k,t}^{ent,new} \left(\mathrm{E}[s_{k,i,t}^{sty}] - \mathrm{E}[s_{k,i,t}^{ent,new}]\right)$.

Figure 7: Decomposing the marginal selection effect, accumulated

Figure 8: Relative to Production

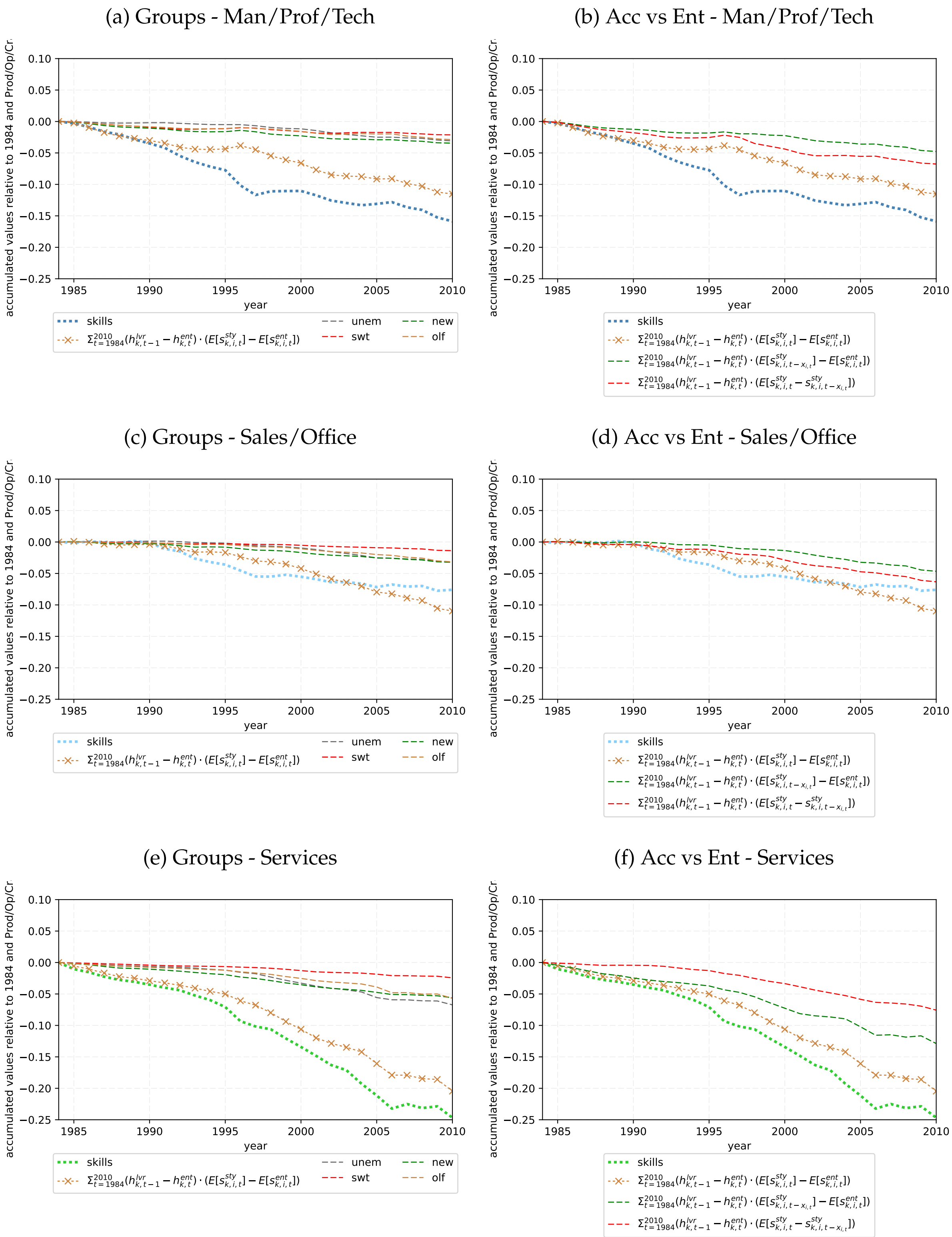
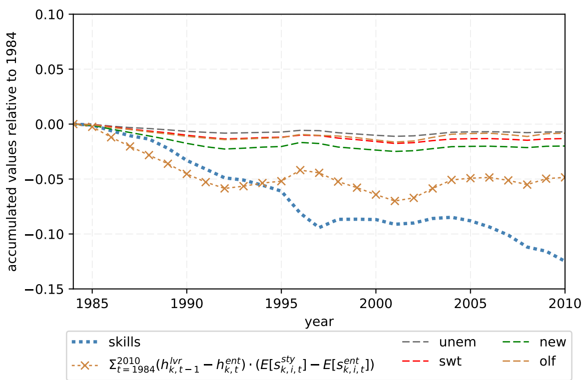
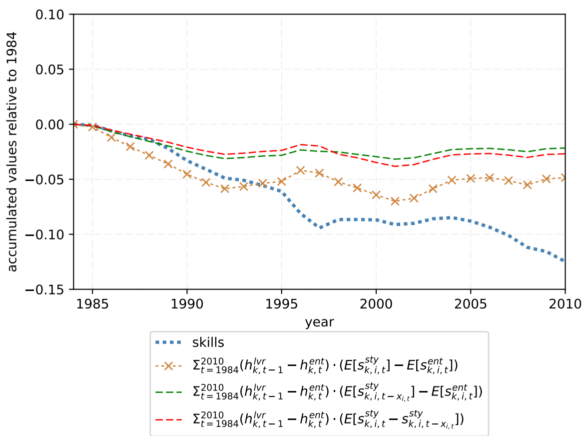


Figure 9: Decomposing the marginal selection effect, accumulated, from skill accumulatiom, i.e. without shocks

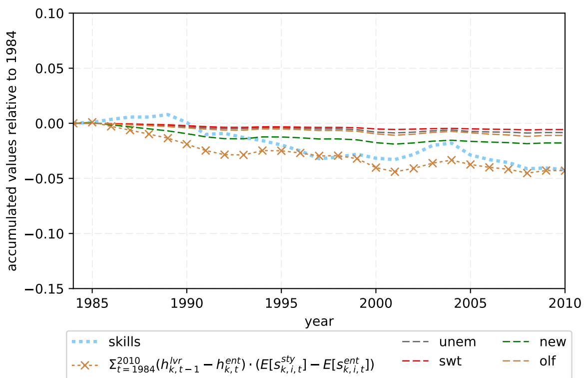
(a) Groups - Man/Prof/Tech



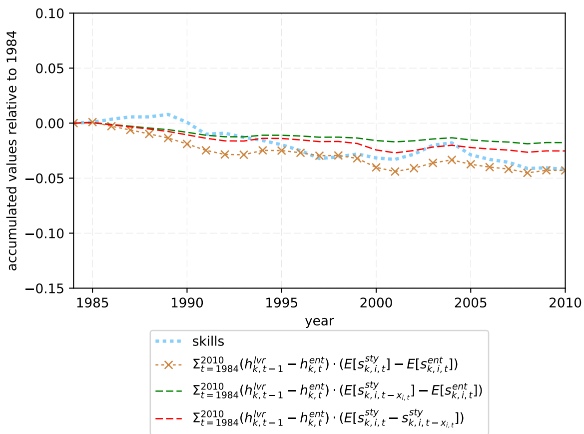
(b) Acc vs Ent - Man/Prof/Tech



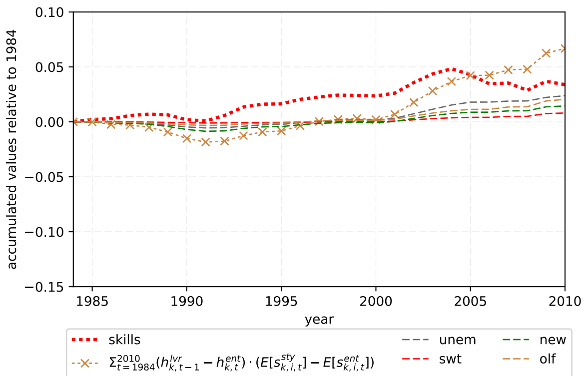
(c) Groups - Sales/Office



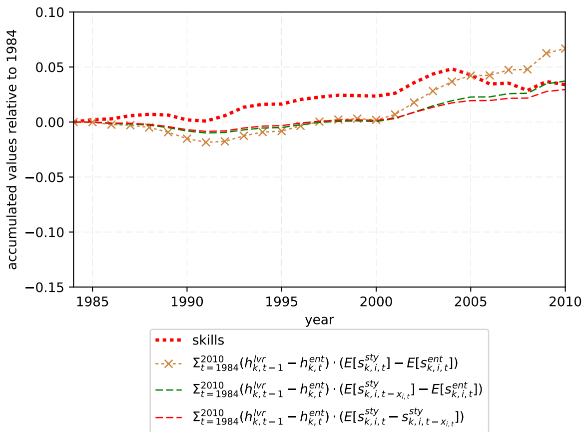
(d) Acc vs Ent - Sales/Office



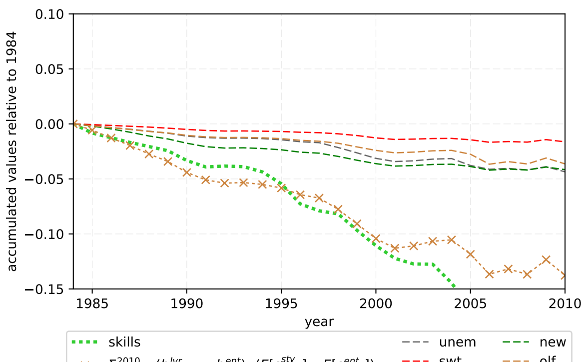
(e) Groups - Prod/Op/Crafts



(f) Acc vs Ent - Prod/Op/Crafts



(g) Groups - Services



(h) Acc vs Ent - Services

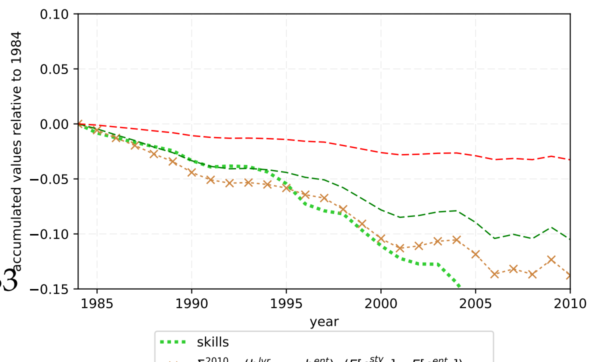
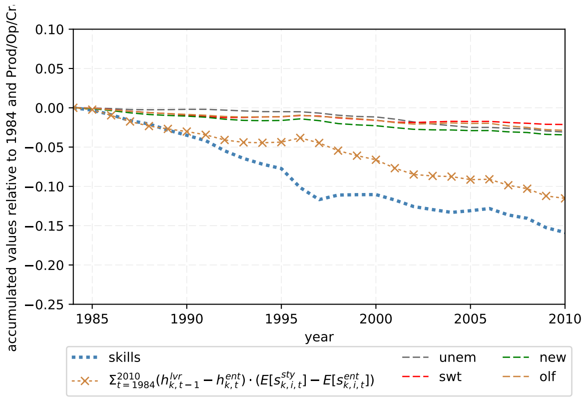
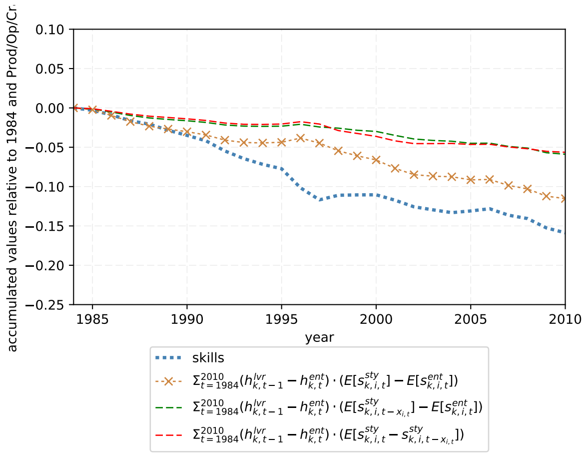


Figure 10: Relative to Production, from skill accumulatiom, i.e. without shocks

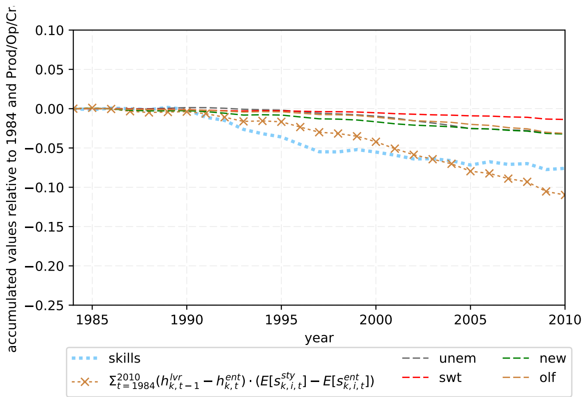
(a) Groups - Man/Prof/Tech



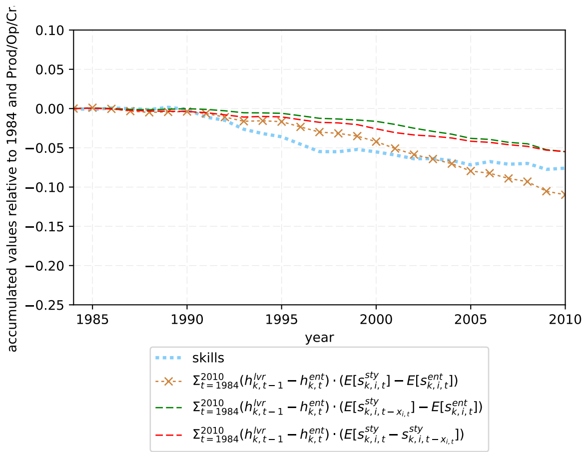
(b) Acc vs Ent - Man/Prof/Tech



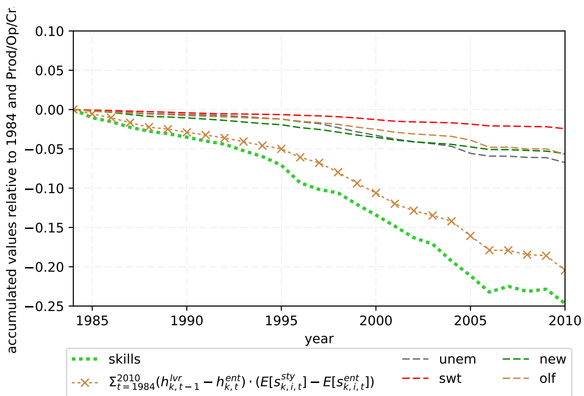
(c) Groups - Sales/Office



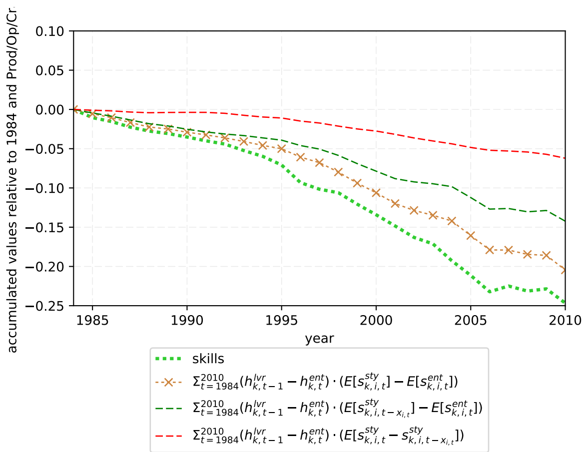
(d) Acc vs Ent - Sales/Office



(e) Groups - Services



(f) Acc vs Ent - Services



5 Evaluation of the Estimation Method and Robustness Checks

5.1 Time-Constant Skills

Many papers assumes time-constant skills. In order to link our estimation method more directly to this large body of evidence, we also show the results from such a specification.

If the workers profession specific skills do not change over time,[24] i.e. $\Delta s_{k,i,t} = 0$ for all k, i, then a linear wage regression of the log change in wages on $\bar{I}_{k,i,t}$ identifies the changing task prices:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \bar{I}_{k,i,t} \Delta \pi_{k,t} \tag{16}$$

If workers do not switch professions, a related specification with profession fixed effects (FE) would also identify $\Delta \pi_{k,t}$ (see Cortes, 2016, for a related approach). If workers do switch, one can also use an "average" FE for destination and origin profession. As we approximated the integral linearly, the average implies weights of 0.5 for destination and origin. The intuition is that switching workers derive one part of their wage gain from the gain in the origin and one part from the destination profession.

Section 5 at the end of the paper provides Monte Carlo evidence that regression (16) identifies the correct task prices, and that thus the approximation (5) is not a material concern in any plausible empirical setting.

6 Conclusions

Long suspected based on Roy theory that marginal workers might be worse than incumbents: Young (2014), Heckman and Sedlacek (1985), McLaughlin and Bils (2001), Gottschalk, Green and Sand (2015), Cavaglia and Etheridge (2017), but we are the first to show how this works empirically via net entry of lower-earning workers and via skill accumulation.

[24]Notice that workers can have different levels of skills but those remain at the same level for the whole lifetime.

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Appendix

A Derivations and Proofs from the Theory

A.1 Derivation of Equation (4)

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

$$dw_{i,t} = \sum_{k=1}^{K} I_k(w_{1,i,t}, ..., w_{k,i,t}, ..., w_{K,i,t})dw_{k,i,t}. \tag{17}$$

To get from marginal changes to absolute ones, hold constant $w_{j,i,t-1} \forall\ j > 1$ at first and integrate (17) with respect to the potential wage in profession 1 :

$$w_{i|w_{1,i,t},w_{2,i,t-1},...} - w_{i|w_{1,i,t-1},w_{2,i,t-1},...} = \int_{w_{1,i,t-1}}^{w_{1,i,t}} I_1(w_{1,i,\tau}, w_{2,i,t-1}, ...)dw_{1,i,\tau}. \tag{18}$$

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

$$\begin{aligned} &w_{i|w_{1,i,t},...,w_{k,i,t},...,w_{K,i,t-1}} - w_{i|w_{1,i,t},...,w_{k,i,t-1},...,w_{K,i,t-1}} = \\ &= \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})dw_{k,i,\tau}. \end{aligned} \tag{19}$$

Summing all of these elements (19) up from $k = 1$ to $k = K$ we get

$$\begin{aligned} &w_{i|w_{1,i,t},...,w_{K,i,t}} - w_{i|w_{1,i,t-1},w_{2,i,t-1},...} = w_{i,t} - w_{i,t-1} = \\ &= \Delta w_{i,t} = \sum_{k=1}^{K} \int_{w_{k,i,t-1}}^{w_{k,i,t}} I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})dw_{k,i,\tau}. \end{aligned} \tag{20}$$

The notation of Equation (4) in the main text is therefore somewhat imprecise, as each integral with respect to $w_{k,i,\tau}$ in (20) in fact holds constant all the other wages.

A.2 Derivation of Equation (6)

Plug the linear interpolation (5) into one integral with respect to $w_{k,i,t}$ in (4)

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

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. Summing up over all k gives Equation (6).

Notice that according to Equation (20) the approximated variable $I_{k,i,\tau}$ is in fact $I_k(w_{1,i,t}, ..., w_{k,i,\tau}, ..., w_{K,i,t-1})$. 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 $I_{k,i,t} = I_k(w_{1,i,t}, ..., w_{k,i,t}, ..., w_{K,i,t})$ in the empirics (and therefore in the linear interpolation), because these are observed in the data. The Monte Carlo simulations in Section C.1 indicate that any approximation error is negligible for identifying the correct task prices estimates.

A.3 Sign of Bias for Instrumental Variables Estimation

In example (10) what remains in the numerator of the bias after instrumenting is Equation (12):

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

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 $\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} > 0$.

A.4 Sign of Bias for the Baseline Estimation

Consider the values entering Equation (13) in each of four cases:

1. if $I_{2,i,t} = I_{2,i,t-1} = 1$, $E(\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 1) = E(\tilde{v}_{2,t}|\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} + \Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} > 0, \tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1} > 0)$. 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 pre-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 (9) entering Equation (13) is larger than the true expectation of the error component $E(\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 1)$. 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 $I_{2,i,t-1} = 0$, $\frac{1}{2}E(\tilde{v}_{2,t}|I_{2,i,t} = 1, I_{2,i,t-1} = 0) = \frac{1}{2}E(\tilde{v}_{2,t}|\Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} > -(\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1}) > 0)$. 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 $I_{2,i,t-1} = 1$, $\frac{1}{2}E(\tilde{v}_{2,t}|I_{2,i,t} = 0, I_{2,i,t-1} = 1) = \frac{1}{2}E(\tilde{v}_{2,t}|\Delta\tilde{\pi}_{2,t} + \tilde{v}_{2,i,t} < -(\tilde{\pi}_{2,t-1} + \tilde{s}_{2,i,t-1}) < 0)$. 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 $I_{2,i,t} = I_{2,i,t-1} = 1$, $0 \cdot E(\tilde{v}_{2,t}|I_{2,i,t} = I_{2,i,t-1} = 0) = 0$ in any case and both the control term entering Equation (13) 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 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 method proposed in the main text. We show that under a realistic model of skill accumulation, this approach requires controlling for the history of workers' job choices, which is difficult to implement in practice. With idiosyncratic skill shocks, classical endogeneity bias occurs that is due to the fixed effects themselves. The results from the Monte Carlo simulations in Section 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). For example, Cortes (2016) specifies

$$w_{k,i,t} = \pi_{k,t} + s_{k,i,t} = \pi_{k,t} + x_{i,t}\gamma_k + \eta_{i,k}, \tag{21}$$

where we have already used the time-varying extension of his model with changing characteristics $x_{i,t}$. These can increase skills differently with age or experience in different professions according to γ_k. In addition, $\eta_{i,k}$ are profession-specific time-invariant skill levels, which will be introduced into the regression by individual-profession(-spell) specific fixed effects. Cortes' estimation equation is therefore:[25]

$$w_{i,t} = \sum_{k=1}^{K} I_{k,i,t}\pi_{k,t} + \sum_{k=1}^{K} I_{k,i,t}\eta_{i,k} + \sum_{k=1}^{K} I_{k,i,t}x_{i,t}\gamma_k + u_{i,t}, \tag{22}$$

In the following, we examine whether estimation of Equation (22) may identify the correct task prices. First, consider the case (7) when skill accumulation is only systematic:

$$\Delta s_{k,i,t} = \sum_{k'=1}^{K} I_{k',i,t-1} \cdot \gamma_{k,k'}, \tag{23}$$

where 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 age $x_{i,t} = 0$) gives

$$s_{k,i,t} = \eta_{i,k} + \sum_{k'=1}^{K} [I_{k',i,t-1} + \ldots + I_{k',i,t-x_{i,t}}]\gamma_{k,k'} = \eta_{i,k} + \sum_{k'=1}^{K}\sum_{\tau=1}^{x_{i,t}} I_{k',i,t-\tau}\gamma_{k,k'}, \tag{24}$$

for $x_{i,t} \geq 1$ and $\eta_{i,k}$ 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 $s_{k,i,t} = \eta_{i,k} + x_{i,t}\gamma_k$ and Estimation (22) identifies the correct task prices, initial endowments, and skill accumulation parameters.

In contrast, if we are not making this assumption and, for example, more realistically allow previous managerial experience to impart more managerial skills than previous experience in production jobs, Equation (24) becomes $s_{k,i,t} = \eta_{i,k} + \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'}$, 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. Wrongly running regression (22) in this case gives an error term $u_{i,t} = \sum_{k=1}^{K} I_{k,i,t}[\sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} -$

[25] 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 (7). However, for demonstration purposes we interpret $x_{i,t}$ as linear in the discussion that follows. Also, other ancillary control variables in Cortes empirical model are omitted for simplicity.

$x_{i,t}\gamma_k]$ which varies with $I_{k,i,t}$ and is thus systematically related to the regressors. This yields biased estimates. The correct fixed effects regression for task prices

$$w_{i,t} = \sum_{k=1}^{K} I_{k,i,t}\pi_{k,t} + \sum_{k=1}^{K} I_{k,i,t}\eta_{i,k} + \sum_{k=1}^{K} I_{k,i,t} \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + u_{i,t}, \tag{25}$$

therefore controls for all previous profession-specific experience separately. While this is conceptually unproblematic to do, its implementation requires high-quality panel data and a long pre-period in order to compute the full experience history of existing workers at the start of the estimation period in $t = 1$. A first-differenced regression such as our Equation (8) is more practical in this respect.

Even the generalized fixed effects approach of Equation (25) obtains a conceptual problem once skill accumulation becomes idiosyncratic across professions, that is, adding $v_{k,i,t}$ on the right-hand-side of Equation (23). Writing this out again gives:

$$s_{k,i,t} = \eta_{i,k} + \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}. \tag{26}$$

The regression error in Equation (25), $u_{i,t} \equiv \sum_{k=1}^{K} I_{k,i,t} \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}$, now systematically depends on the full history of previous idiosyncratic skill shocks, which influence current choices (i.e. the regressors in Equation (25)). Therefore, we get a classical endogeneity bias. One might expect that the sector-experience-specific controls in regression (25) largely address this problem, similar to our differenced approach (8). But this is not the case.

True, in the pre-period ($\pi_{k,1} = const$, $\forall k$), regression (25) estimates the expectation of the systematic accumulation and the idiosyncratic shocks conditional on the history of profession choices:

$$E\left(\sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau} | \{I_{k',i,t-1}\}\right) = \sum_{k'=1}^{K} x_{k',i,t}\hat{\gamma}_{k,k'}, \tag{27}$$

where $\{I_{k',i,t-1}\}$ is our shorthand notation for the full history of worker i's profession choices from entry into the labor market to $t-1$. However, the choices themselves (e.g. $I_{k',i,t} = \mathbb{1}[\pi_{k',t} + s_{k',i,t} = \pi_{k',t} + \eta_{k',i} + \sum_{k'=1}^{K} x_{k',i,t}\gamma_{k,k'} + \sum_{\tau=0}^{x_{i,t}-1} v_{k',i,t-\tau} > \pi_{k,t} + s_{k,i,t}, \forall k]$) not only depend on the full history of accumulation and skill shocks, but also on initial skill endowments $\eta_{k,i}$. Given the history of choices, the expectation we form about the skill shocks therefore differs with the endowments (i.e. in general $E(\sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}|\{I_{k',i,t-1}\}, \{\eta_{k,i}\}) \neq E(\sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}|\{I_{k',i,t-1}\})$). Intuitively, if a worker with a high initial endowment of managerial skills chooses to work in that profession at some point in his career, our expectation about his skill shocks for that profession is lower than for a worker with low initial managerial skill endowment and exactly the same (history of) professional choice.

Plugging the conditional expectation function (27) into Estimation (25)

$$w_{i,t} = \sum_{k=1}^{K} I_{k,i,t}\pi_{k,t} + \sum_{k=1}^{K} I_{k,i,t}\eta_{i,k} + \sum_{k=1}^{K} I_{k,i,t} \sum_{k'=1}^{K} x_{k',i,t}\hat{\gamma}_{k,k'} + error_{i,t}, \tag{28}$$

still gives a endogeneity problem even if $E(\sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau}|\{I_{k',i,t-1}\})$ does not change from the pre-period, because the expectation of the error

$$error_{i,t} = \sum_{k=1}^{K} I_{k,i,t} \left[\sum_{k'=1}^{K} x_{k',i,t} \gamma_{k,k'} + \sum_{\tau=0}^{x_{i,t}-1} v_{k,i,t-\tau} - \sum_{k'=1}^{K} x_{k',i,t} \hat{\gamma}_{k,k'} \right], \tag{29}$$

conditional on $\{I_{k',i,t-1}\}$ systematically varies with the regressor $\sum_{k=1}^{K} I_{k,i,t} \eta_{i,k}$. Therefore, even a maximally flexible model of average skill accumulation and idiosyncratic shocks as a function of the worker's professional experience obtains classical endogeneity bias because, conditional on that experience, the expected shocks covary (negatively) with the initial skill endowments. In order to address this, one would need to empirically model the skill accumulation and idiosyncratic shocks as a function of workers' professional experience *as well as* their fixed effects. This would be econometrically highly complicated.

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 and the distribution of skill shocks. We start with a dataset in which skill accumulation is only systematic and then add idiosyncratic skill shocks. We also compare the performance of our estimator to the alternative estimation strategy with multiple fixed effects, which we analyzed theoretically in the previous section.

In order to make the simulations as realistic as possible and to assess the potential size of any biases, we generate datasets for the Monte Carlo simulations that aim to replicate important moments in the actual SIAB data. For example, the age distribution in the Monte Carlo datasets is generated from draws out of the SIAB age distribution (draws from a multinomial with probabilities equal to frequencies of being born in a certain year).[26] Initial skills were drawn from a distribution that is similar to the initial wage distribution of the SIAB once task prices are removed. The same is true for the idiosyncratic skill shocks in Section C.2. Table A1 summarizes the parameter choices that we made in the results reported below. The comparison of our Monte Carlo samples with the actual SIAB is presented in the respective Sections C.1 and C.2.

Table A1: Chosen Parameters for the Monte Carlo Samples

parameter	set value
$N \times T$	10000×36
Replications	8
(Start year, base year, end year)	(1975, 1984, 2010)
Prices	['siab_prices_3_3_est_prices_ols_age_acc']
Methods	['3_3_est_prices_ols_age_acc']
Skills	dict_keys(['with_accumulation', 'without_accumulation'])
Initial skills	['normal', 2.8, 0.5]
Skill shocks in k	[['uniform', 0], ['gumbel', 1]]
Skill shocks across k	['uniform', 0, 0]
Age	21 - 50
Price shocks	['uniform', 0, 0]

Notes: TBW.

The first three rows of Table A1 show that in each replication we drew 5,000 workers for 40 periods (i.e. from year 1975 to 2014), and that we replicated this 30 times. Since we match the birth year distribution in the SIAB, new age 21 agents enter and old age 50 agents leave the sample every period. For the underlying task prices, we chose that they were constant in the pre-period (periods 1–10 or years 1975–1984) and that there is a trend break in task price growth in 1991 to match the fact that wages in the SIAB grow much slower after that point in time (e.g. see Figure 1(b)). Other options we have tried were same trend growth and differing trend growth in the pre-period and the results were as discussed in Section 3.2, that is, we could identify the correct task price changes and the correct accelerations/decelerations of task price growth, respectively.

[26] The same is true for the occupational distribution within professions. For that, a random draw from the empirical SIAB distribution is done so that we can merge the task data to the monte carlo datasets, since in our model agents choose professions but not detailed occupations for which we need the task data.

The remainder of Table A1 is concerned with initial skills, skill accumulation, and skill shocks. In what is shown below, we chose initial log skills to be normally distributed with a mean and standard deviation equal to the actual distribution of initial wages less task prices in the SIAB. Idiosyncratic skill shocks are either zero (Section C.1) or extreme value distributed (C.2) with a standard deviation set to 15 times the average absolute value of task price changes over the whole dataset.[27] Just as in the main SIAB estimation, age in the Monte Carlo sample ranges from 21 to 50 so that we have skill accumulation parameters that differ by current and last period's profession as well as decadal age group (i.e. 21–30, 31–40, 41–50). We chose these skill accumulation parameters to approximate the life-cycle profiles of Figure 2, that is, coefficients are larger for younger workers and for workers in managerial and professional as well as sales and office professions (for exact numbers see Table A1).

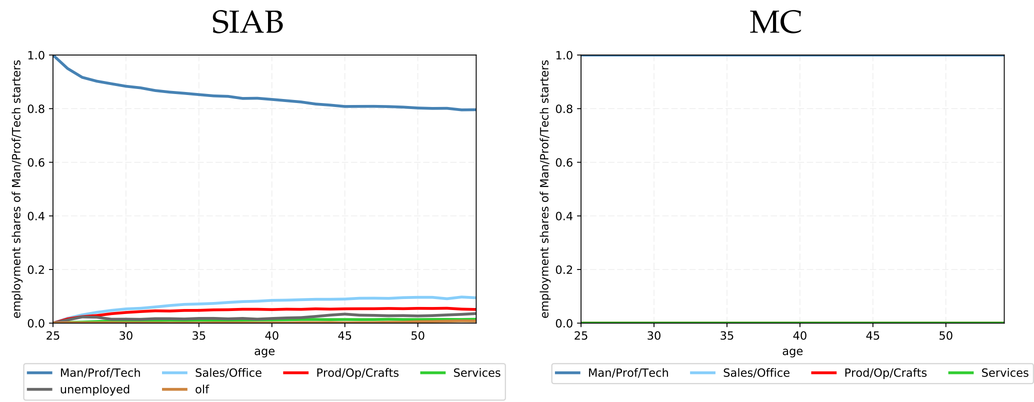
C.1 Only Systematic Skill Accumulation

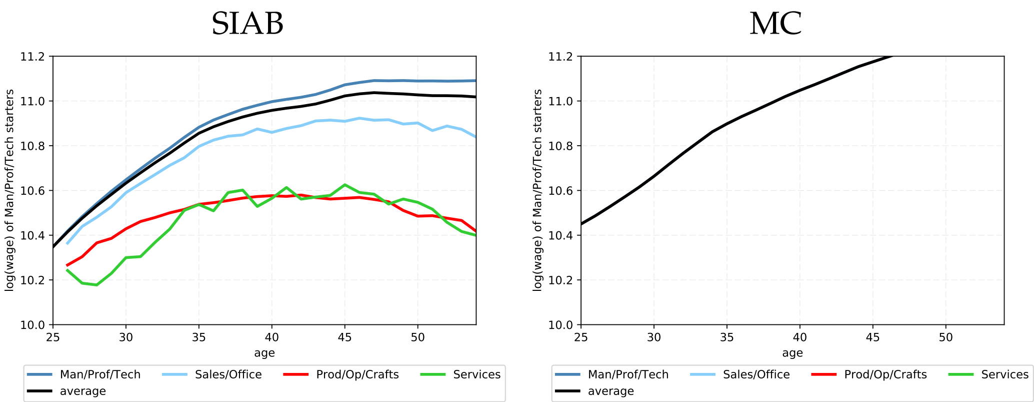
For each replication, we generate a panel dataset with agents who possess skills and face task prices in the four professions. Based on these, the agents decide every period where to work in order to maximize their wage. In this subsection, we start with the case presented in Section 3.2 of the main paper. That is, skills accumulate systematically over time depending on observables such as where the agent worked and his age.

[27] We have also added skill shocks that are common to all professions ("Skill shocks accross k" in the table) and used distribution functions with correlated skill shocks (such as the normal distribution) and found similar results to those presented below.

- Skills: with-accumulation

- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: uniform ($\mu = 0,\ \sigma = 0 \cdot \sigma^{\text{SIAB}}_{\Delta \log(w_i)} = 0.0 = 0.0 \cdot \max_k(\sigma_{\Delta \pi_k^{\text{true}}})$





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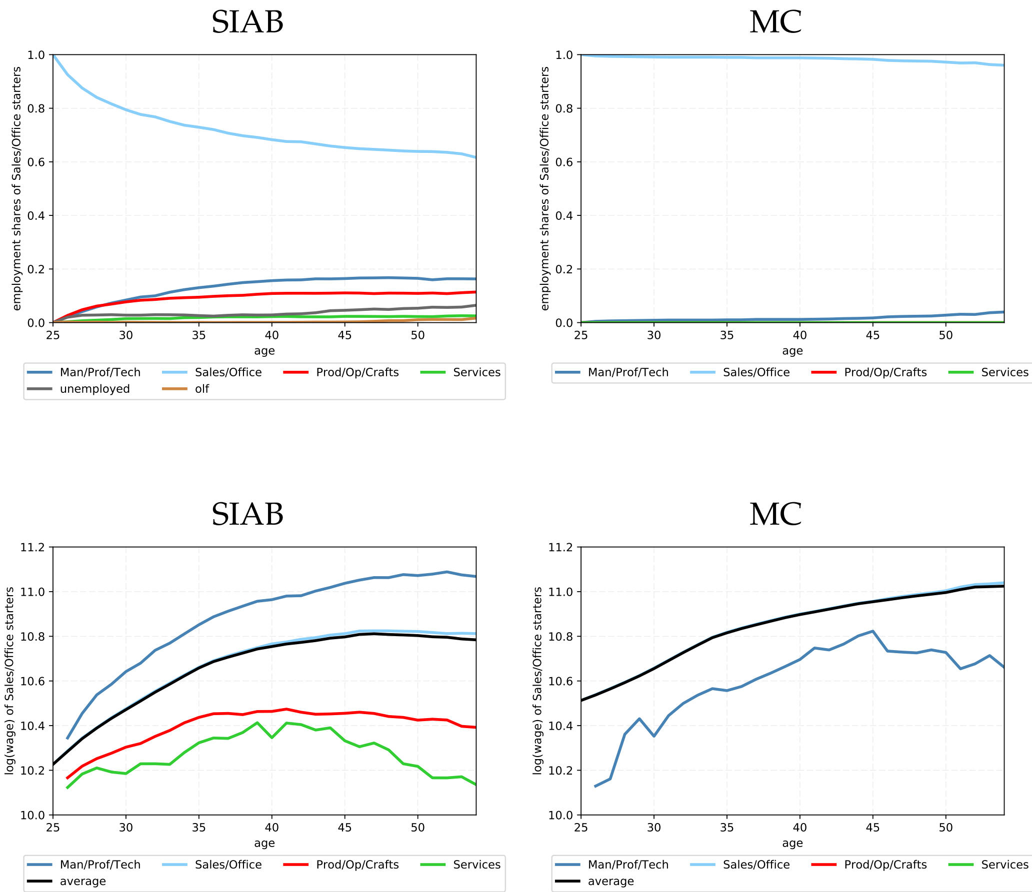

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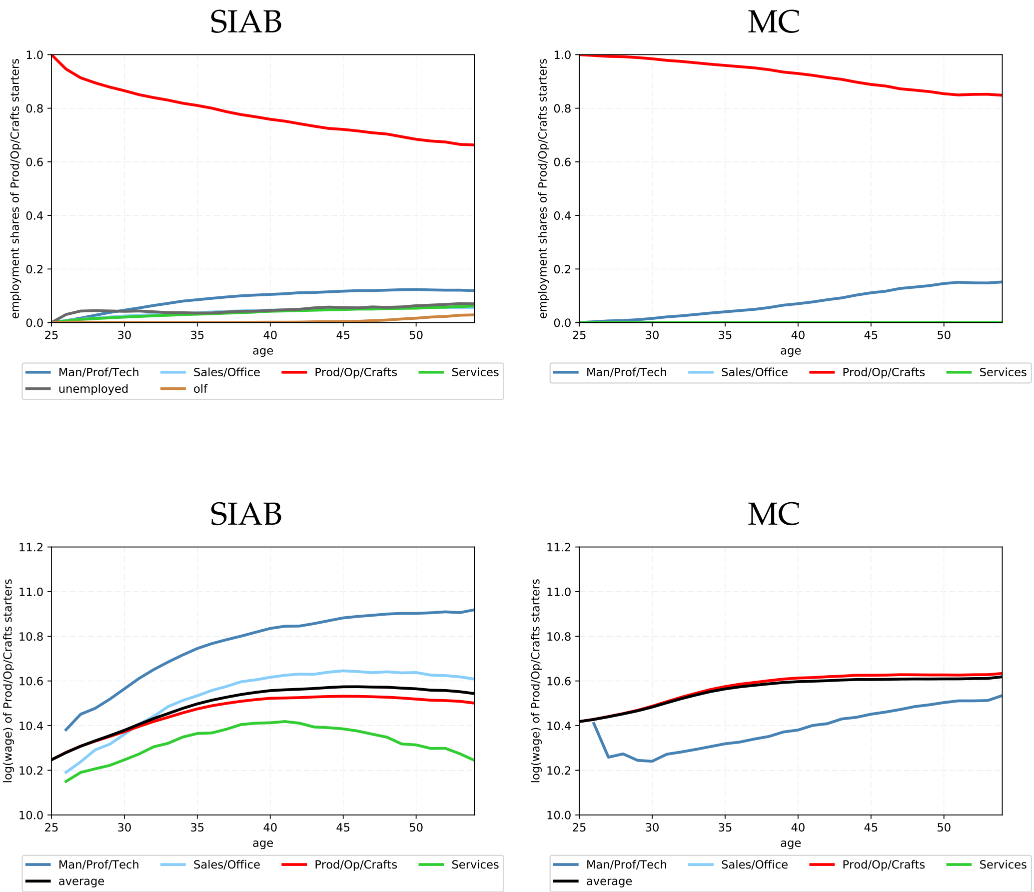

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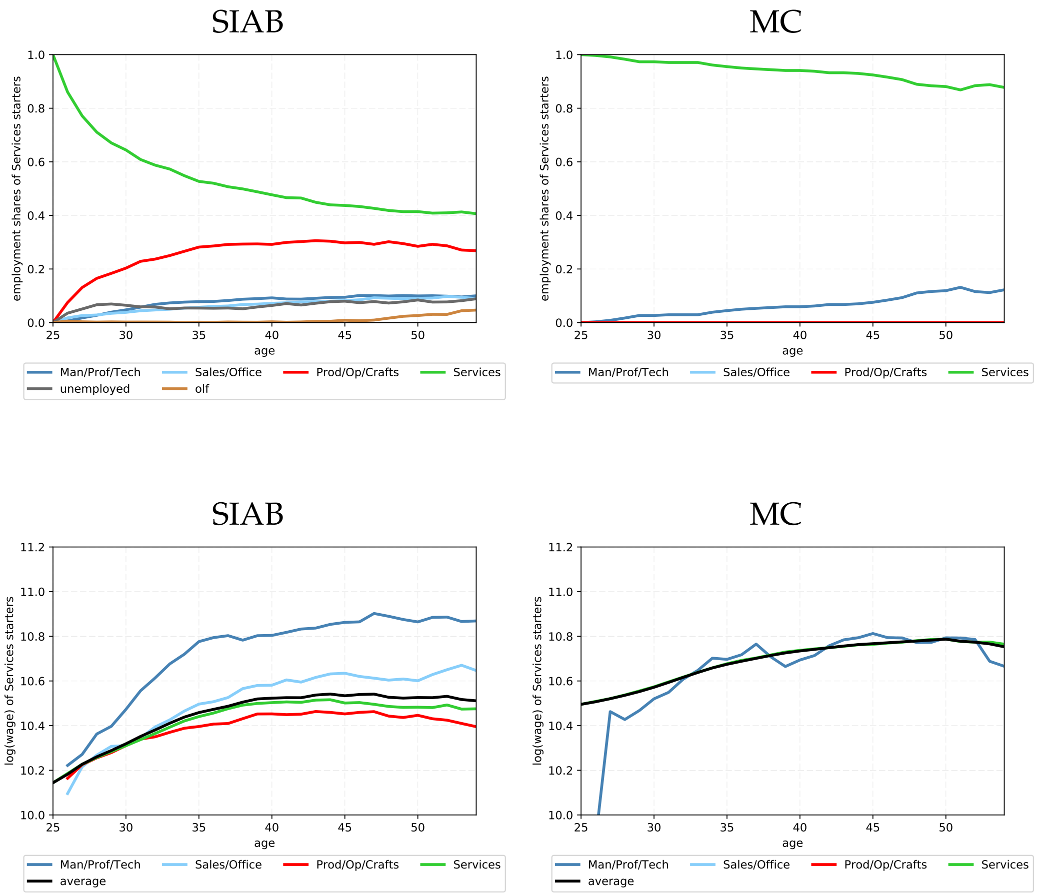

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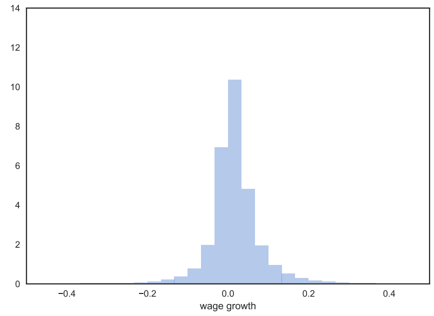
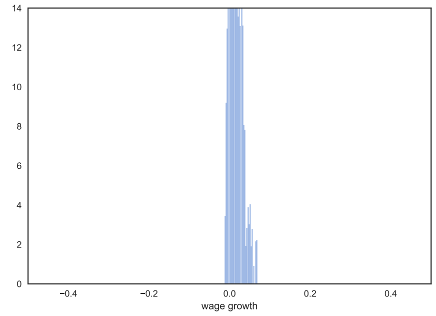
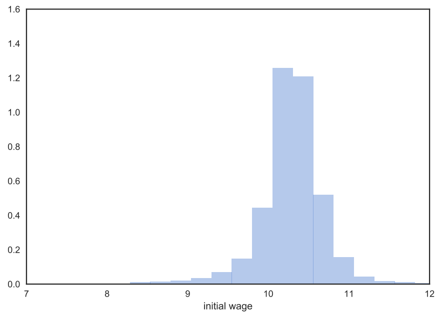
SIAB



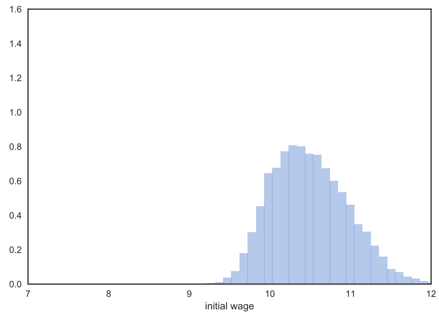
MC



SIAB



MC



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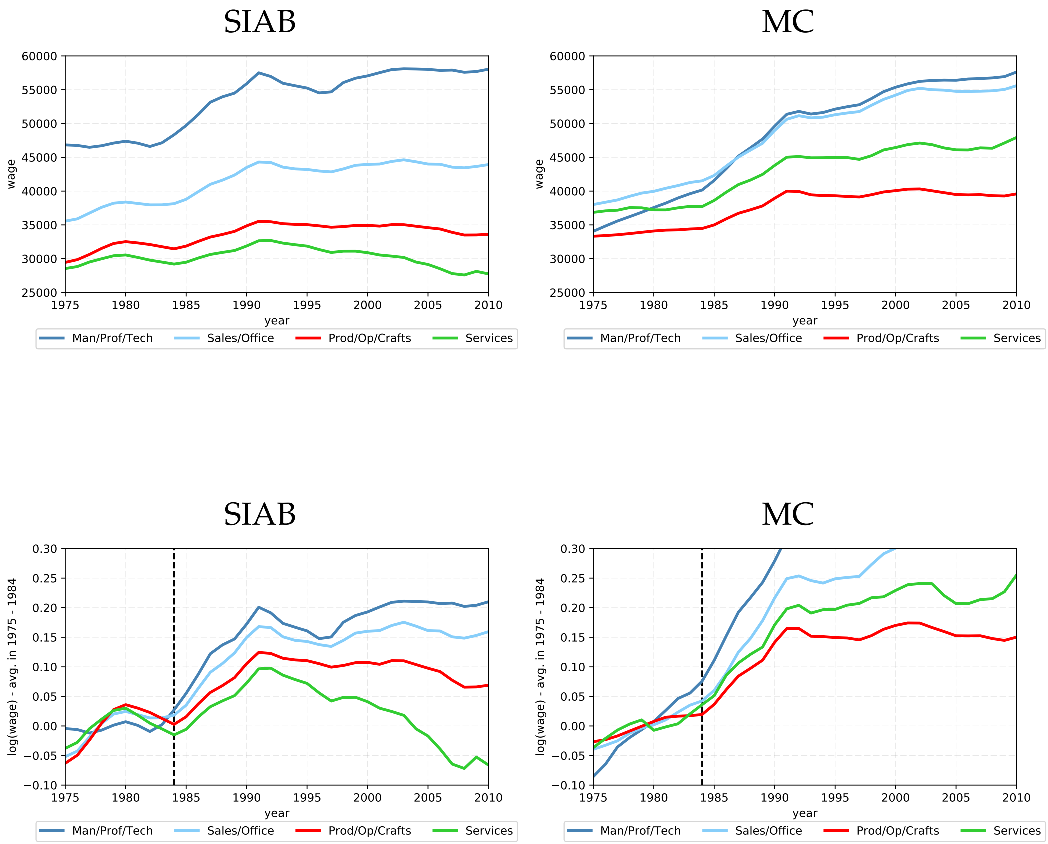

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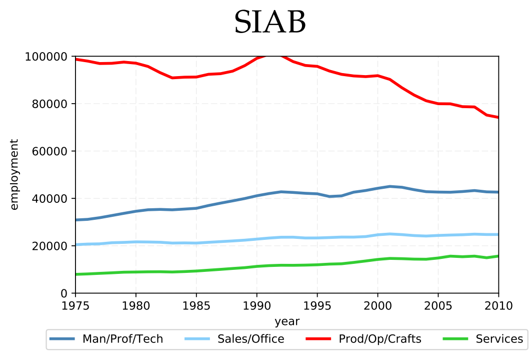
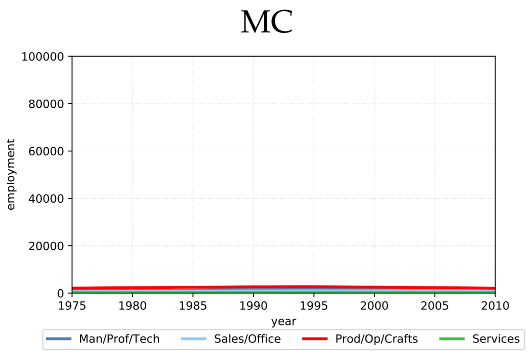
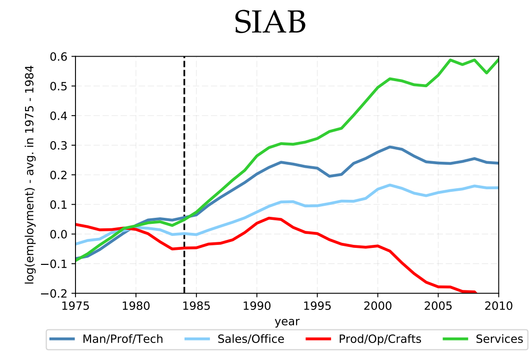
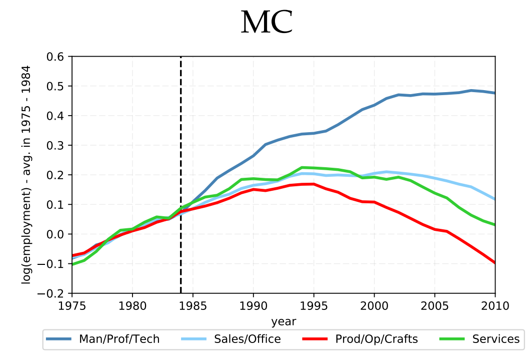
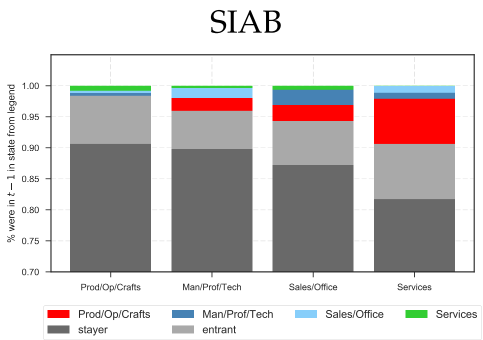

SIAB
employment
year
Man/Prof/Tech
Sales/Office
Prod/Op/Crafts
Services


MC
employment
year
Man/Prof/Tech
Sales/Office
Prod/Op/Crafts
Services


SIAB
log(employment) - avg. in 1975 - 1984
year
Man/Prof/Tech
Sales/Office
Prod/Op/Crafts
Services


MC
log(employment) - avg. in 1975 - 1984
year
Man/Prof/Tech
Sales/Office
Prod/Op/Crafts
Services


SIAB
% were in t − 1 in state from legend
Prod/Op/Crafts
Man/Prof/Tech
Sales/Office
Services
stayer
entrant

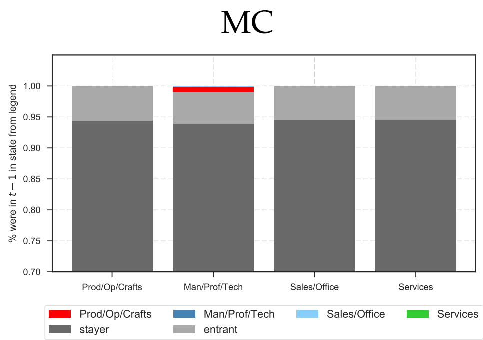

MC
% were in t − 1 in state from legend
Prod/Op/Crafts
Man/Prof/Tech
Sales/Office
Services
stayer
entrant

Figure **??** shows important summary plots of the Monte Carlo data used in the estimation compared to the actual SIAB data.[28] In the first row, we see the age distribution in the SIAB and the sample data match quite well. In the second row, initial log wages in reality are more left-skewed and feature stronger kurtosis than in the generated data using normality, but the mean and standard deviation are the same. Wage growth, conditional on the systematic skill accumulation, is of course homogeneous and zero in the case with no idiosyncratic shocks (Panel (f)).

The remainder on the first page of Figure **??** shows workers' profession switches and long run changes in employment and average wages. Without idiosyncratic skill shocks, agents in the Monte Carlo sample switch much less than in the actual SIAB data, and switches are essentially uni-directional and driven by skill accumulation for managerial and professional and partly sales and office occupations as well as rising task prices for those occupations. The rising task prices for managerial/professional, sales/office, and services occupations lead to a polarization of the employment structure similar to the actual SIAB data, but the development of average wages in occupations is not matched very well (for this, compare the bottom row of Figure A10).

Finally, the second part of Figure **??** depicts the implied individual employment and wage dynamics in the Monte Carlo dataset. Compared to Figure 2 from the SIAB, there is less switching of occupations (only toward managerial and professional) and less heterogeneity of earnings over agents' life cycles. This underscores our argument from Section 2.3 that a realistic panel data model of employment and wage dynamics needs to contain unobservable drivers of the idiosyncratic differences (i.e. shocks) in these variables.

[28]Overall employment and average wage trends are averages over all repetitions whereas distributions like wage growth and switches are for the first Monte Carlo dataset only.

Dataset is MC
- Skills: with-accumulation
- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: uniform ($\mu = 0,\ \sigma = 0 \cdot \sigma^{\mathrm{SIAB}}_{\Delta \log(w_i)} = 0.0 = 0.0 \cdot \max_k(\sigma_{\Delta \pi_k^{\mathrm{true}}})$

Figure A1: Monte Carlo Results Using Our Approach (22) (Only Systematic Skill Accumulation)

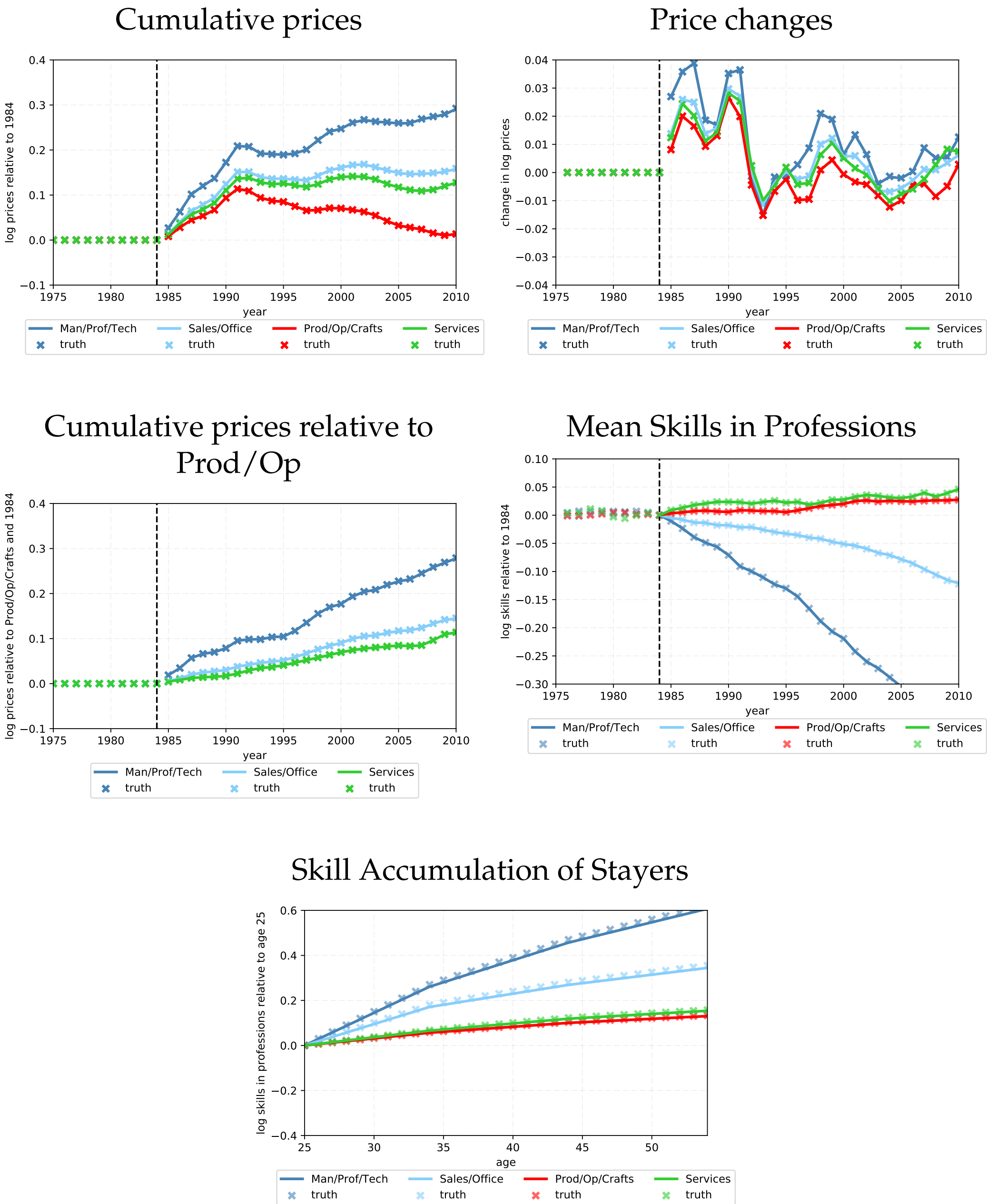


Figure **??** presents the Monte Carlo results using our baseline estimation (8). We see in the top left panel that the true task prices fed into the Monte Carlo sample (dotted lines) and their estimates (solid lines) closely overlap. The same is true in Panel (b) for the task prices relative to production and crafts as a reference profession.[29] The implied selection of skills into the different professions from the estimated task prices is also identified correctly. Consistent with our discussion around Figure 1, Panels (c) and (d), skills in the shrinking production and crafts profession rise while (relative) skills in the growing other three professions decline.

These results therefore support the argument in theory Section 3.2 that the baseline estimation method is able to identify the correct task prices in a setting with multi-dimensional skills and self-selection into sectors as well as a rich and realistic model of skill accumulation that depends on prior sector choices, age, and their differential effects on current professions. Estimation (8) also correctly identifies the skill accumulation parameters. Plotting the accumulated skills $\hat{s}^{acc}_{k,i,t}$ for stayers in Panel (d) of Figure **??**,[30] we see that the estimation both identifies the ranked skill accumulation by profession (e.g. managerial highest and services lowest) and its concavity in age.

[29]Remember from the discussion in Section 3.2 that when task prices in the pre-period are not constant but grow at the same rate, relative task prices can still be identified.

[30] That is, for $k \epsilon \{1, 2, 3, 4\}$,

$$\hat{s}^{acc}_{k,i,t} = \begin{cases} \hat{\gamma}_{k,k,1} \cdot (a_{i,t} - 20) & \text{if } 21 \leq a_{i,t} \leq 30 \\ \hat{\gamma}_{k,k,1} \cdot 10 + \hat{\gamma}_{k,k,2} \cdot (a_{i,t} - 30) & \text{if } 31 \leq a_{i,t} \leq 40 \\ \hat{\gamma}_{k,k,1} \cdot 10 + \hat{\gamma}_{k,k,2} \cdot 10 + \hat{\gamma}_{k,k,3} \cdot (a_{i,t} - 40) & \text{if } 41 \leq a_{i,t} \leq 50. \end{cases}$$

Dataset is MC
- Skills: with-accumulation
- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: uniform ($\mu = 0,\ \sigma = 0 \cdot \sigma^{\mathrm{SIAB}}_{\Delta \log(w_i)} = 0.0 = 0.0 \cdot \max_k(\sigma_{\Delta \pi^{\mathrm{true}}_k})$

Figure A2: Monte Carlo Results Using Multiple Fixed Effects Approach (22) (Only Systematic Skill Accumulation)

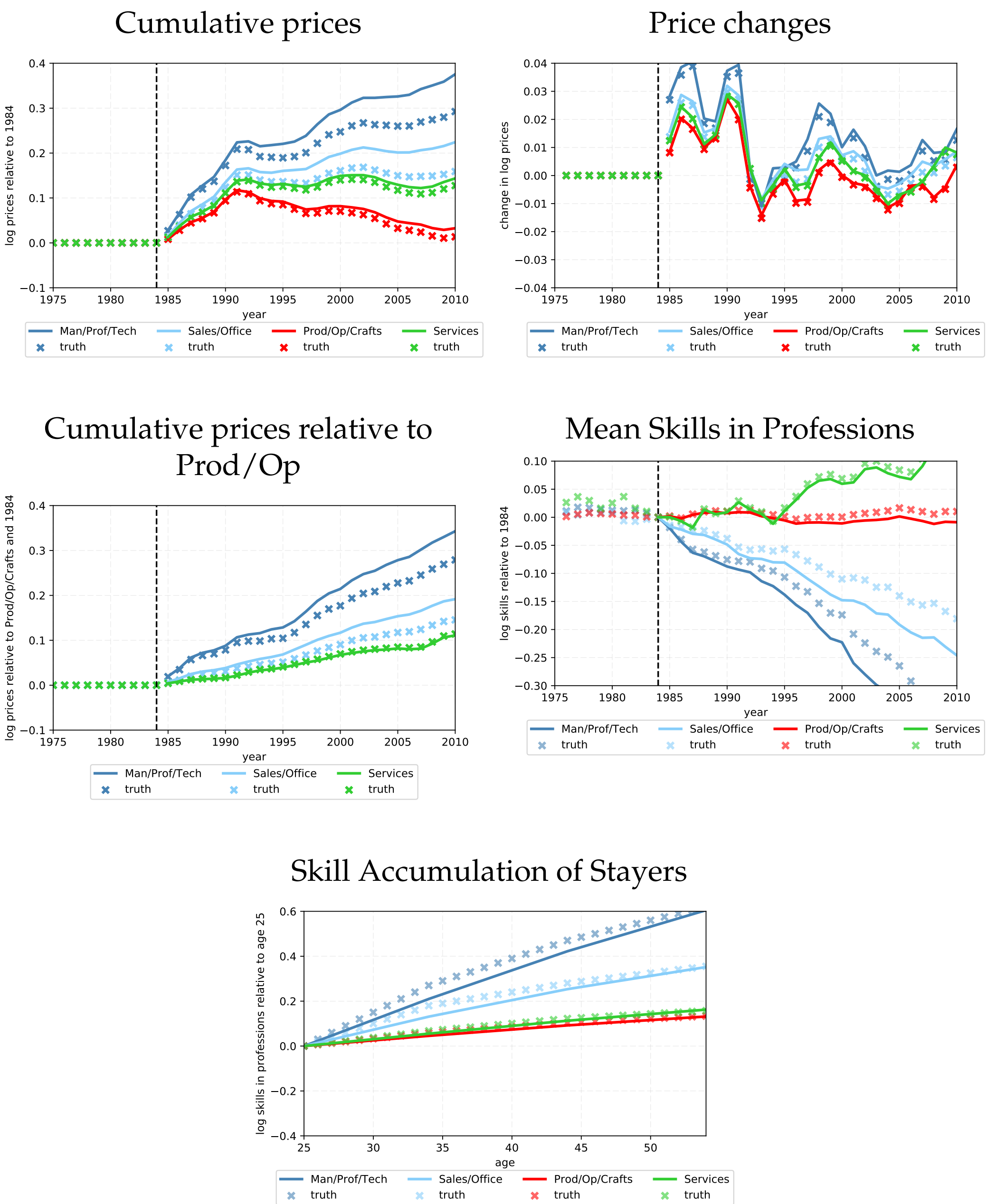


Figure **??** compares these results to the multiple fixed effects estimation (22) as an alternative, which we theoretically discussed in the previous section. We see that the estimates from profession-year dummies controlling for agent-profession fixed effects and age group interacted with profession are not able to identify the correct task prices and consequently also the implied skill selection. Even the relative task prices are substantially biased in the case of managerial and professional occupations and sales and office occupations. Moreover, the implied skill selection (Panel (c)) and the estimated skill accumulation $\hat{s}^{acc}_{k,i,t}$, again plotted for profession stayers,[31] are also substantially biased.

Therefore, our theoretical argument from Section B is vindicated that in order for the fixed effects approach to work in a setting with rich and realistic skill accumulation, one would need to track and flexibly control for the *entire history* of agents' occupational choice. This, as we argued above, is difficult to do in practice with panel datasets of limited time series dimension and/or attrition and reappearance of individuals over time.

C.2 Including Idiosyncratic Skill Shocks

In this section, we add idiosyncratic skill shocks to the data generating process in the Monte Carlos. This corresponds to the case discussed in Section 3.3 of the main text and it leads to more realistic worker switching, wage growth, and career dynamics more generally. As predicted in the theory, our baseline estimation method moderately underestimates the absolute changes in relative task prices, while the bias in the alternative multiple fixed effects model is more severe and cannot be signed.

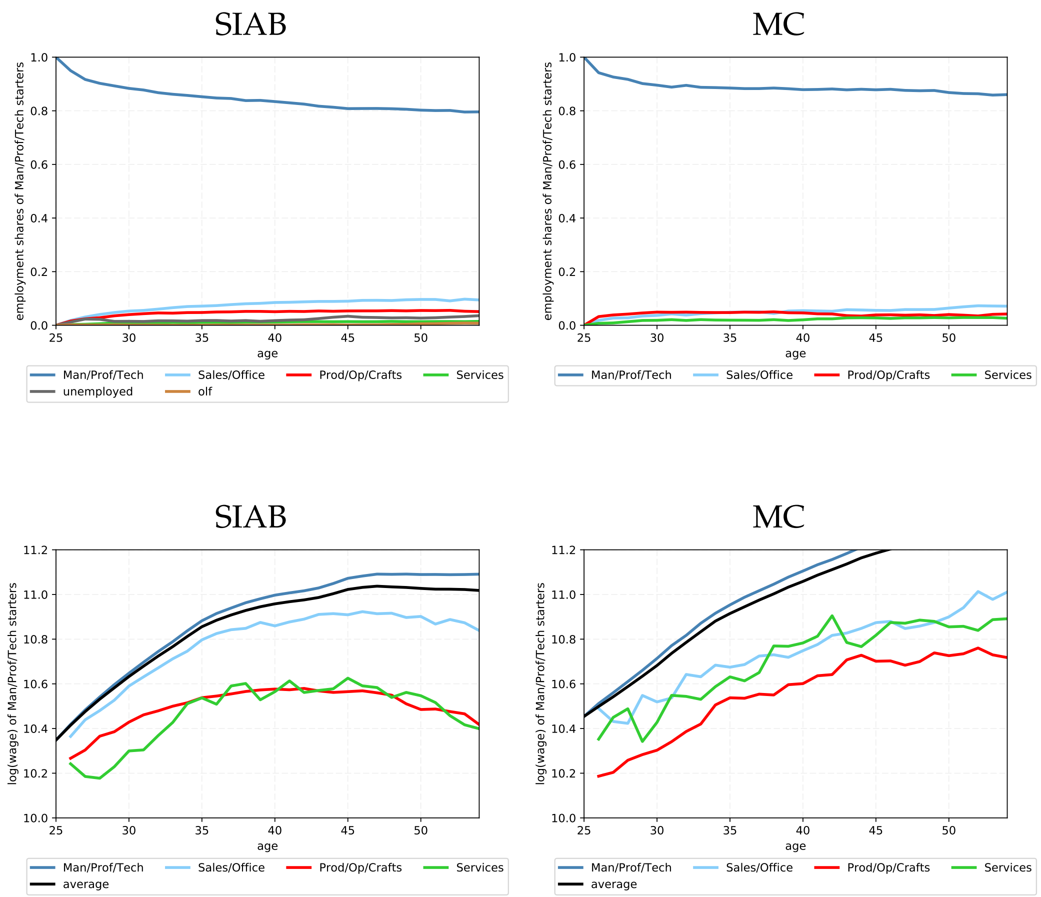
[31] In the standard fixed effects estimation (e.g. Cortes, 2016), which we follow here, an age interaction is used in Equation (22). Hence, for all $k\epsilon\{1, 2, 3, 4\}$,

$$\hat{s}^{acc}_{k,i,t} = \hat{\gamma}_{k,1} \cdot \mathbb{1}[21 \leq a_{i,t} \leq 30] + \hat{\gamma}_{k,2} \cdot \mathbb{1}[31 \leq a_{i,t} \leq 40] + \hat{\gamma}_{k,3} \cdot \mathbb{1}[41 \leq a_{i,t} \leq 50].$$

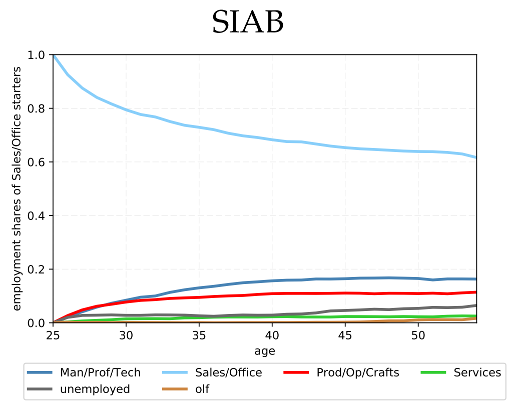
- Skills: with-accumulation

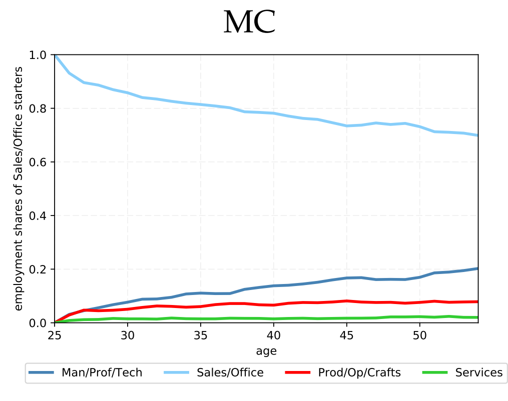
- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: gumbel ($\mu = 0,\ \sigma = 1 \cdot \sigma^{\text{SIAB}}_{\Delta \log(w_i)} = 4.093 = 0.0 \cdot \max_k(\sigma_{\Delta \pi_k^{\text{true}}})$

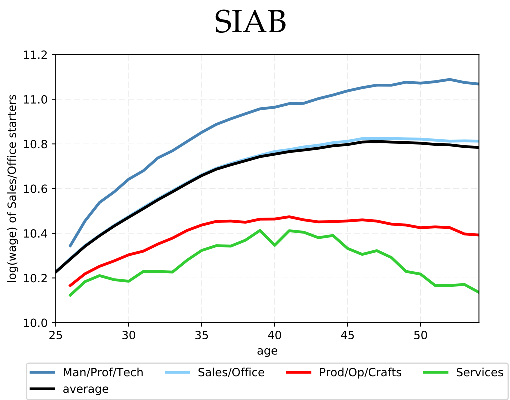
Figure A3: Comparison of SIAB and Monte Carlo (MC) Datasets (Including Idiosyncratic Skill Shocks)

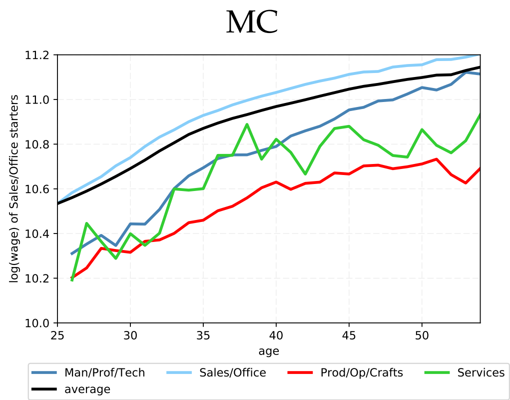


...continue to compare this specification against SIAB on the next page...

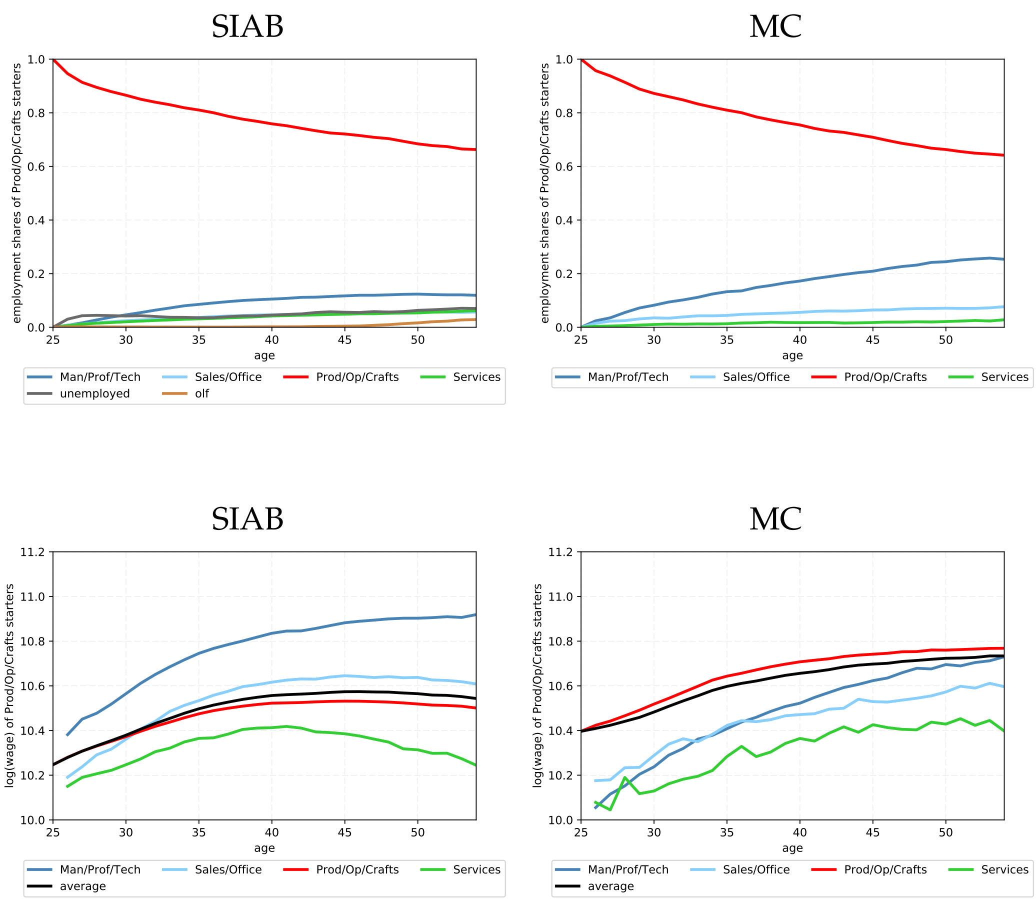




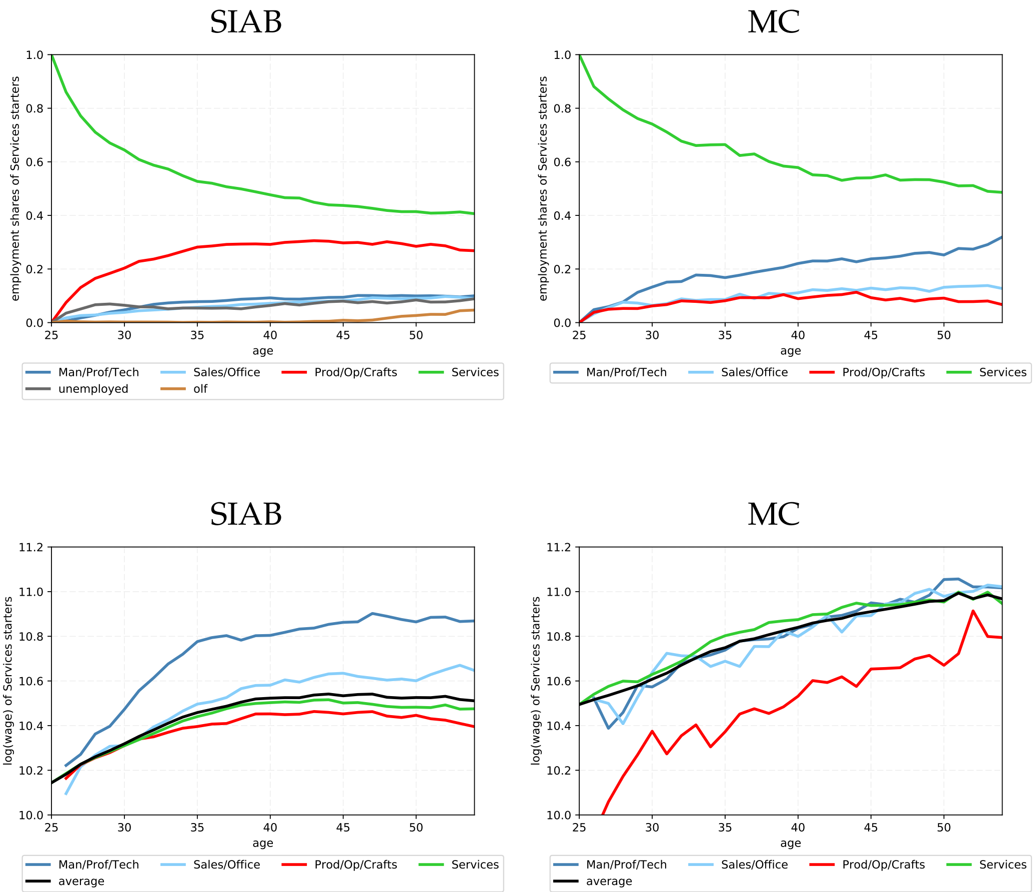




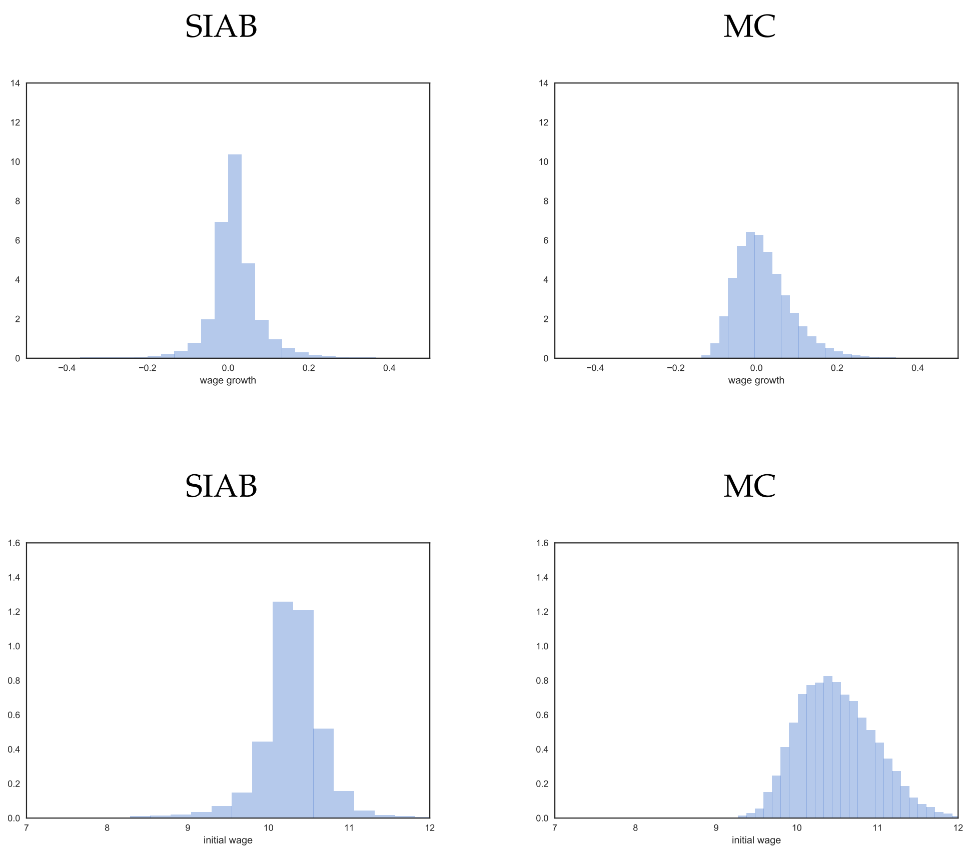
...continue to compare this specification against SIAB on the next page...



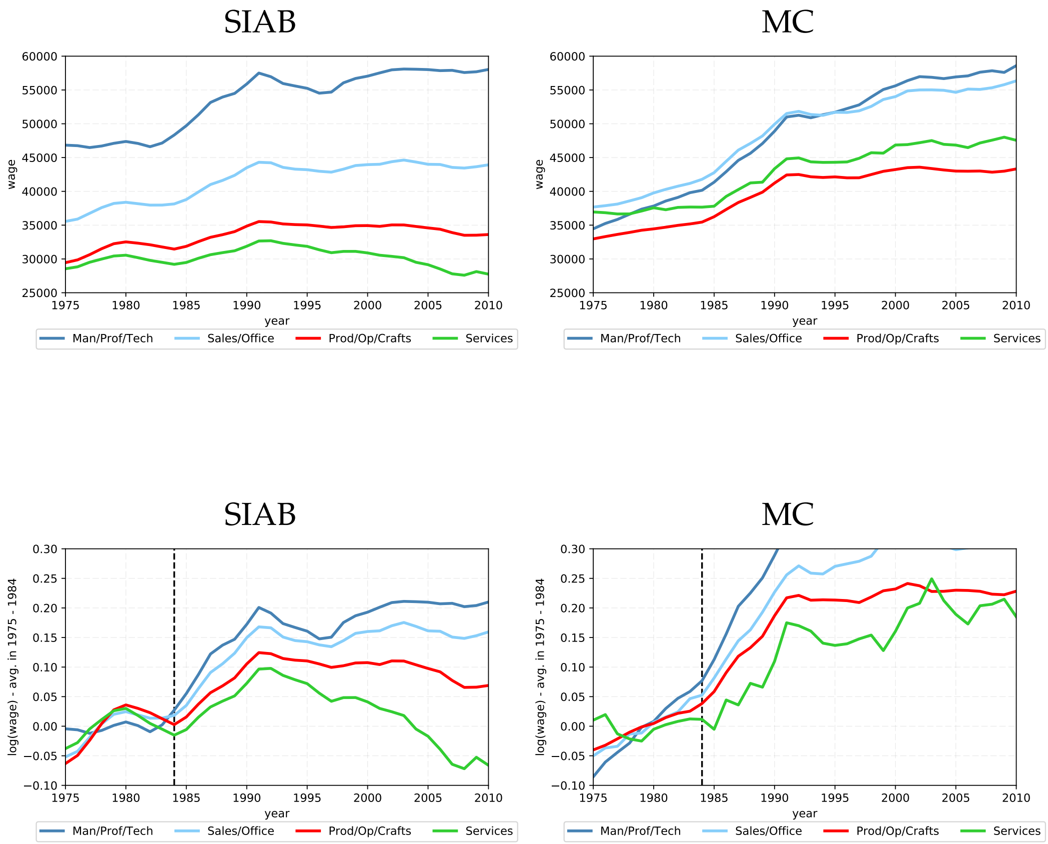
...continue to compare this specification against SIAB on the next page...



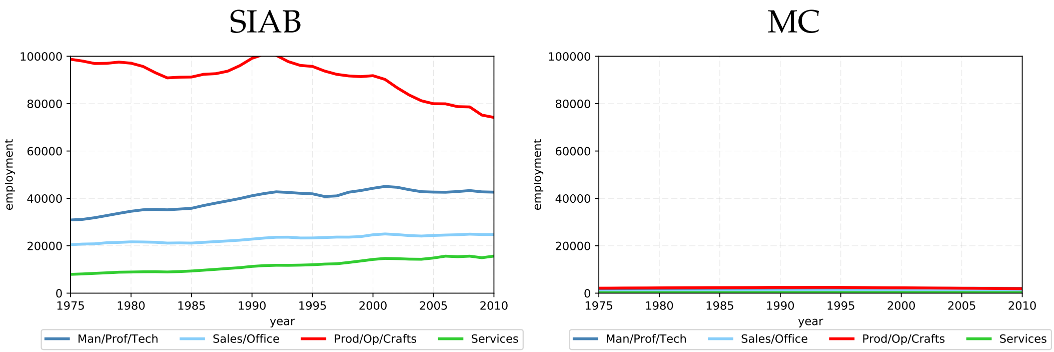
...continue to compare this specification against SIAB on the next page...

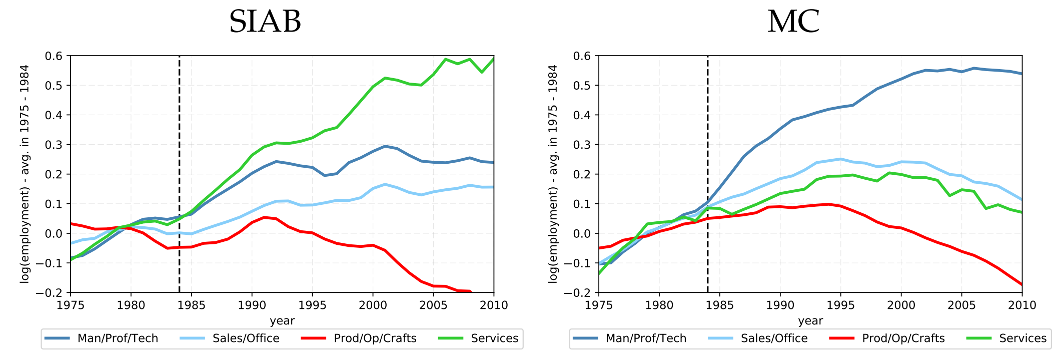


...continue to compare this specification against SIAB on the next page...



...continue to compare this specification against SIAB on the next page...





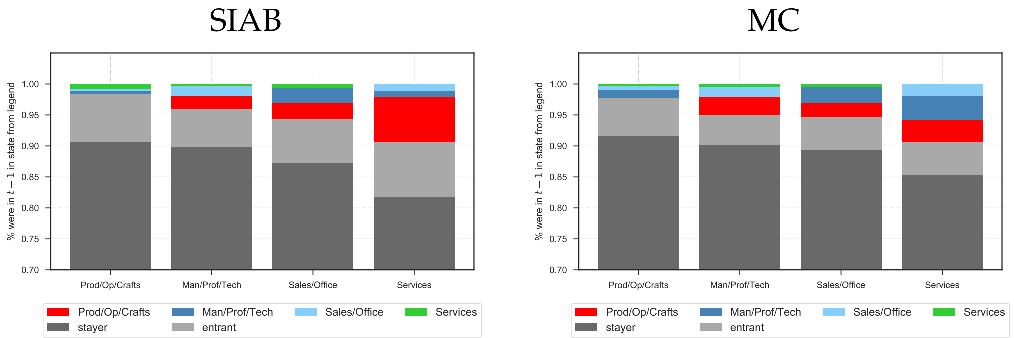


Figure **??** shows the summary plots of the Monte Carlo data when we add idiosyncratic skill shocks. The age and initial wage distributions are similar to above and to the SIAB (first two rows), but the distribution of period-to-period wage growth, conditional on systematic skill accumulation, is now non-degenerate (third row compared to Figure **??** above). It also has the same mean and standard deviation as in the actual SIAB data, although the third and fourth moments, skewness and kurtosis, are still somewhat different. Moreover, the amount of switching between professions, and especially multi-directionality (e.g. from manager to services and vice versa), is now almost as large as in the SIAB (fourth row). The polarization of the overall employment structure and the change in average wages across professions is similar to the case without idiosyncratic shocks.

The second page of Figure **??** shows that, although they still do not match the SIAB (Figure 2) perfectly, the individual career dynamics are now closer to it in important respects. First, employment changes are more common and they are not only toward managerial but also toward sales and even slightly toward production professions over the career. Wage dynamics are realistic in the sense that stayers or switchers to managerial or sales earn more and stayers or switchers to production and services tend to earn less than average starters in the respective professions, a key fact documented in Figure 2.

Dataset is MC
- Skills: with-accumulation
- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: gumbel ($\mu = 0,\ \sigma = 1 \cdot \sigma^{\mathrm{SIAB}}_{\Delta \log(w_i)} = 0.077 = 4.093 \cdot \max_k(\sigma_{\Delta \pi_k^{\mathrm{true}}})$

Figure A4: Monte Carlo Results Using Baseline Estimation (8) (Including Idiosyncratic Skill Shocks)

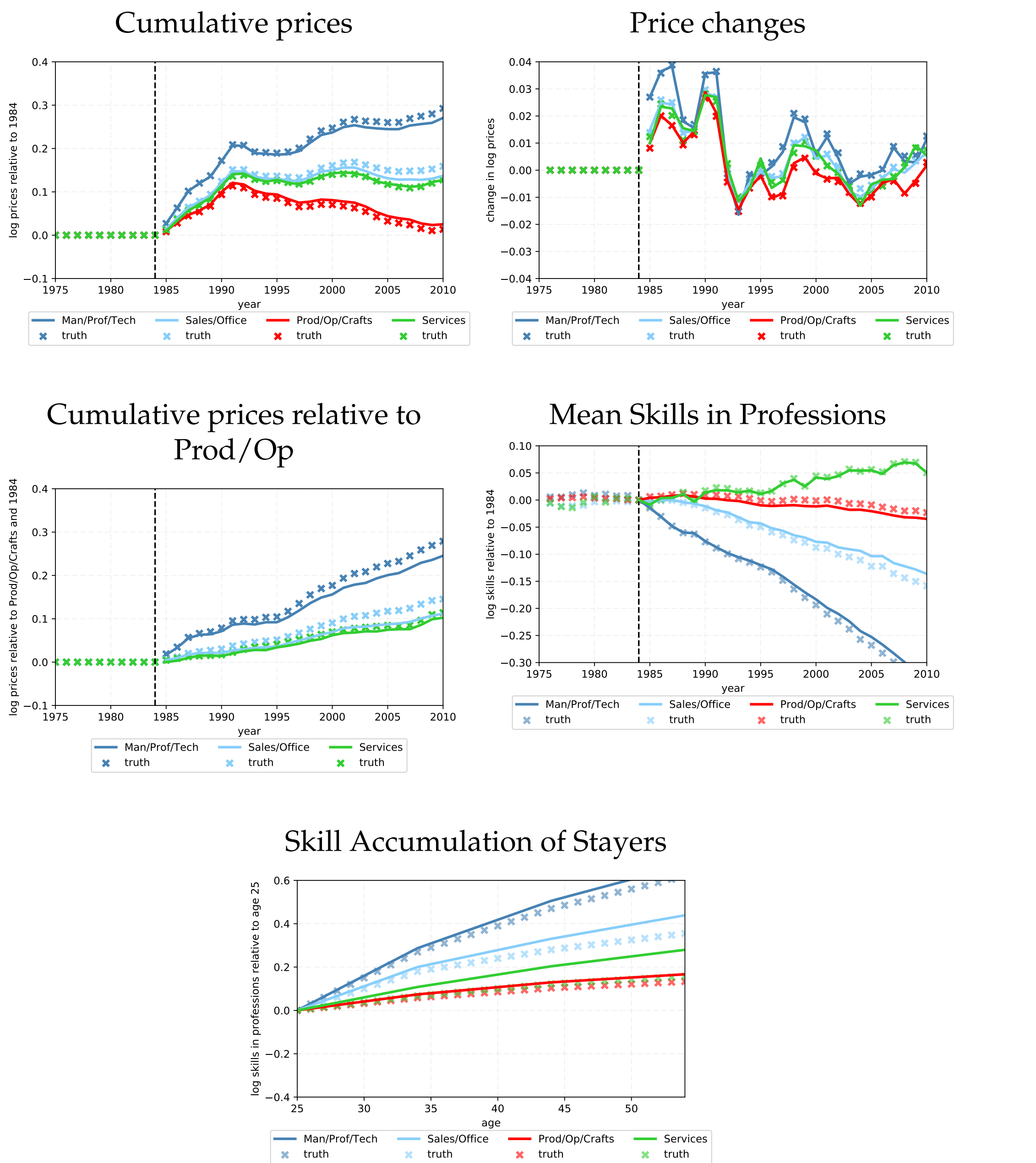


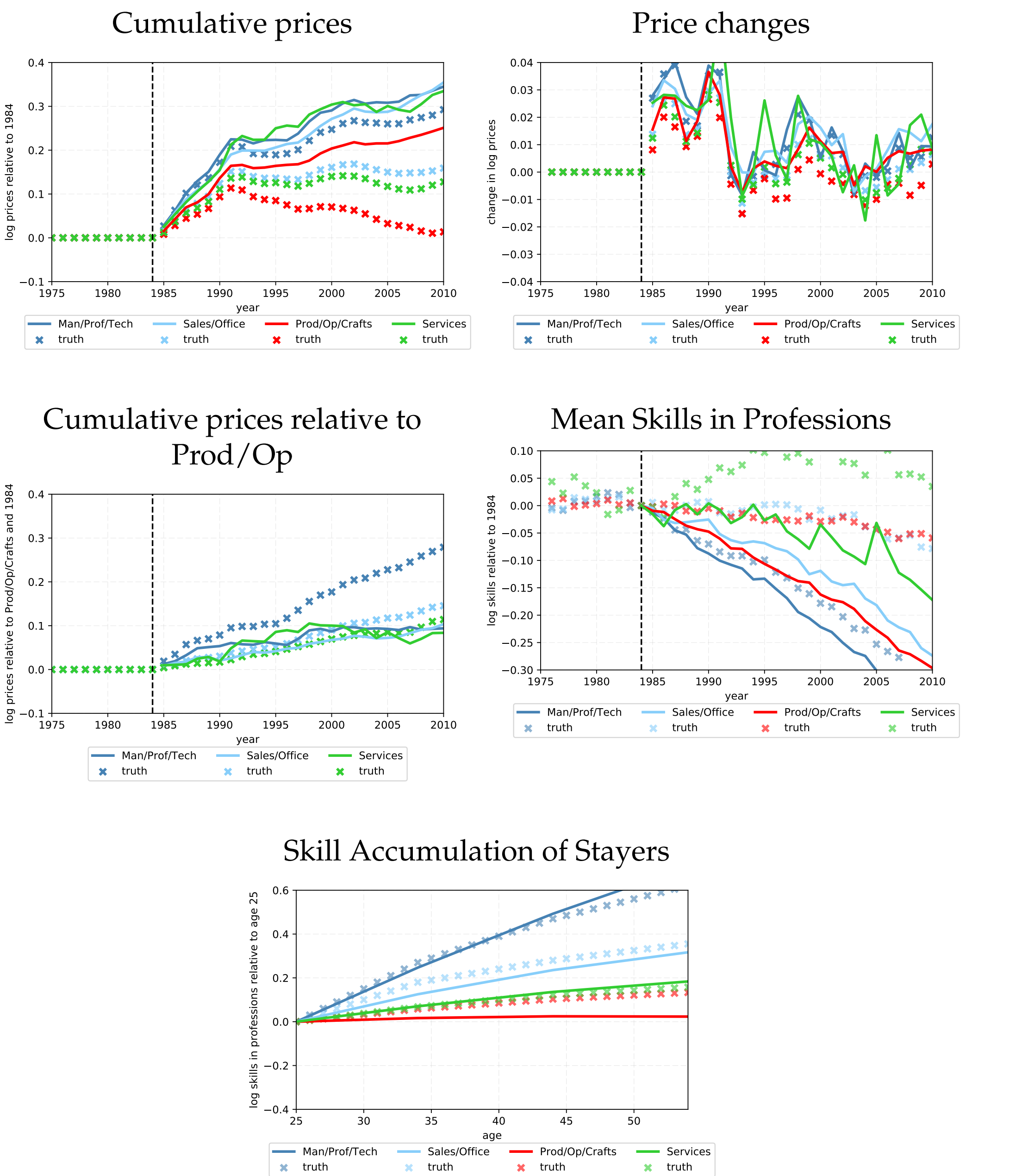
Figure **??** presents the estimation results under idiosyncratic skill shocks using our baseline model (8). In Panel (a) the absolute task price estimates are close but no exactly the truth and the task prices relative to production and crafts are all moderately underestimated, with only a slight bias for services and a more substantial one for managerial and professional occupations. These results therefore support the prediction from Section 3.3 and theoretical Appendix A.4 that our estimation method under idiosyncratic skill shocks should provide a close lower bound for the extent of true changes in *relative* task prices.

The bottom panels of Figure **??** plot the implied skill selection into professions and the estimated skill accumulation. The strongly rising skill selection into production and crafts is slightly underestimated, while the skill selection into the other professions is quite well matched. As already discussed in the main text (Section 3.3), with idiosyncratic shocks estimated coefficients $\hat{\gamma}_{k,k',a}$ are not the structural $\gamma_{k,k',a}$ parameters anymore, but provide the average wage growth due to skill accumulation *including from shocks and switching* of workers of age a who worked in k' last period and in k this period. Plotting $\hat{s}^{acc}_{k,i,t}$ again (same construction as in footnote 30), therefore unsurprisingly does not perfectly match the true accumulated skill of the respective profession stayers (Panel (d)).

Dataset is MC

- Skills: with-accumulation
- Prices: siab-prices-3-3-est-prices-ols-age-acc
- Professions: myopic
- Shock Distribution: gumbel ($\mu = 0,\ \sigma = 1 \cdot \sigma^{\text{SIAB}}_{\Delta \log(w_i)} = 0.077 = 4.093 \cdot \max_k(\sigma_{\Delta \pi_k^{\text{true}}})$

Figure A5: Monte Carlo Results Using Multiple Fixed Effects Approach (22) (Including Idiosyncratic Skill Shocks)



Finally, Figure **??** reports the estimation results using the alternative multiple fixed effects estimation (22) with idiosyncratic skill shocks. We see that the estimated task prices (Panel (a)) are far from the truth while their relative values (Panel (b)) are somewhat less (but still severely) biased and the bias cannot be signed. These findings are as predicted, since classical endogeneity bias enters through the back door with idiosyncratic skill shocks via the individual fixed effects in the regression (see formal argument in Appendix B). The implied skill selection into sectors (Figure **??**, Panel (c)) and the estimated skill accumulation (Panel (d)) are consequently also very different from their true values in the Monte Carlo dataset.

Overall, we conclude from this exercise that the estimation method performs as we analytically predicted in Section 3 of the main text and the respective theoretical appendices. Our baseline regression is able to identify the correct changes in task prices in a rich model of skill accumulation across destination and origin sectors and age groups. When idiosyncratic skill shocks are added to this model, the method still performs quite well, providing estimates close to the truth and a lower bound to the true changes in relative task prices. The alternative, and equally straightforward, estimation method using multiple fixed effects, however, already struggles with the systematic skill accumulation. When idiosyncratic skill shocks are added, the estimates are very different to those from the baseline model and substantially further from the truth.

D Further Empirical Results

D.1 Alternative Decomposition of Skill Selection

This section provides an alternative decomposition of the changing skill selection to Section 4.2.

Decompose the skills plotted in Figure 6 based on leavers' marginal selection instead of entrants:[32]

$$\begin{aligned} \mathrm{E}[s_{k,i,t}|I_{k,i,t}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1}=1] = & \underbrace{\left(1-h_{k,t}^{ent}\right)\cdot \mathrm{E}[\Delta s_{k,i,t}^{sty}]}_{\textbf{learn}\text{ing: accumulation of stayers}} \\ & + \underbrace{h_{k,t}^{ent}\cdot\left(\mathrm{E}[s_{k,i,t}^{ent}]-\mathrm{E}[s_{k,i,t-1}^{lvr}]\right)}_{\textbf{churn}\text{ing: difference entrants, leavers}} \\ & + \underbrace{\left(h_{k,t-1}^{lvr}-h_{k,t}^{ent}\right)\cdot\left(\mathrm{E}[s_{k,i,t-1}^{sty}]-\mathrm{E}[s_{k,i,t-1}^{lvr}]\right)}_{\textbf{marg}\text{inal }\textbf{sel}\text{ection}} \end{aligned} \tag{30}$$

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

- If aggregate skill accumulation in profession k, $\mathrm{E}[\Delta s_{k,i,t}^{sty}]$, is high, the first term is large.
- But this leads to a large difference in skills $\left(\mathrm{E}[s_{k,i,t}^{ent}]-\mathrm{E}[s_{k,i,t-1}^{lvr}]\right)$ btw entrants and leavers and the impact of churning will be high.
- If turnover in the profession ($h_{k,t}^{ent}$) rises, 1 *and* 2 falls because accumulated skill is lost to churning.

These are effects that are not related to sector growth or decline, and often 1 and 2 cancel out (see Figure A6 below). However, effect 3 is directly related to sector growth:

- $\left(\mathrm{E}[s_{k,i,t-1}^{sty}]-\mathrm{E}[s_{k,i,t-1}^{lvr}]\right)$ is difference between stayers and marginal workers (leavers in this case), which is strongly positive as seen in the bottom row of Figure 1.
- Therefore, term 3 is negative if the sector grows ($h_{k,t-1}^{lvr}-h_{k,t}^{ent}<0$), positive if it shrinks. Notice that this latter effect does not depend on the estimated task prices!

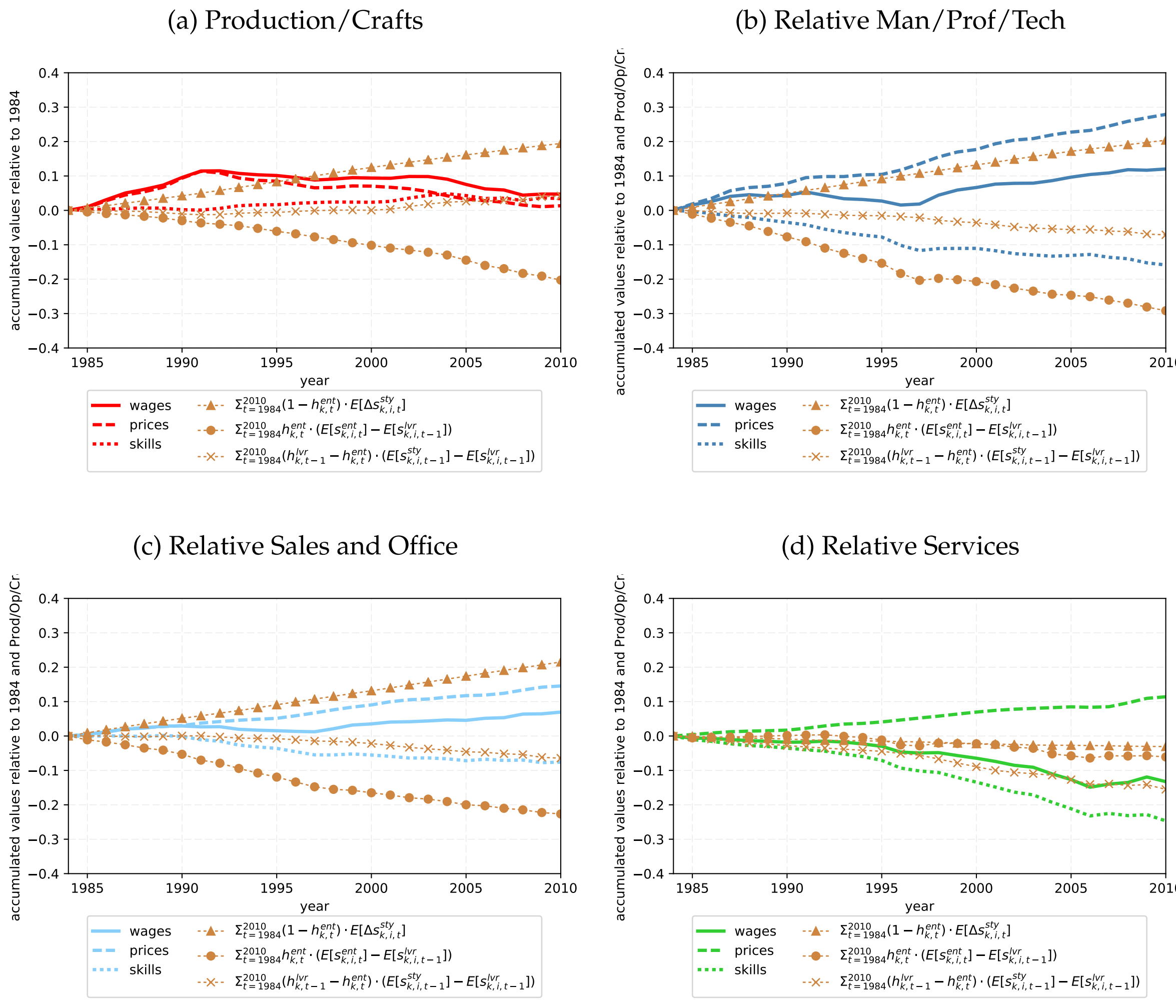
We see in Figure 6 that effects 1 and 2 (everything relative to production, here!) largely cancel out for the three sectors and that the change in the skill selection is very similar to effect 3, especially in the case of managerial and professional (Panel (a)) and Services (Panel (c)). This effect is the marginal selection, which is due to sector growth (it is zero for a stable sector). So this is a mechanical selection effect that stems from managerial, sales, and services growth relative to production and which largely matches the overall change in skill selection from our estimation!

Figure XX focuses on the marginal selection effect based on leavers, which we found again largely drives sectors' changing skill selection (Figure A6). First, we decompose

[32]The intermediate steps are $\mathrm{E}[(1-h_{k,t}^{ent})s_{k,i,t}^{sty}+h_{k,t}^{ent}s_{k,i,t}^{ent}]-\mathrm{E}[(1-h_{k,t-1}^{lvr})s_{k,i,t-1}^{sty}+h_{k,t-1}^{lvr}s_{k,i,t-1}^{lvr}]=$

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

Figure A6: Average Wages, Task Prices, and Implied Skills in Professions. Decomposition of Skills into Accumulation, Churning, and Marginal Selection



the contributions of sector switchers, leavers to unemployment or out of the labor force during their careers, and from retirees. That is, one can rewrite

$$\mathrm{E}[s^{lvr}_{k,i,t-1}] = h^{lvr,swt}_{k,t-1}\mathrm{E}[s^{lvr,swt}_{k,i,t-1}] + h^{lvr,UO}_{k,t-1}\mathrm{E}[s^{lvr,UO}_{k,i,t-1}] + h^{lvr,rtr}_{k,t-1}\mathrm{E}[s^{lvr,rtr}_{k,i,t-1}],$$

where the shares of leavers who are profession switchers $h^{lvr,swt}_{k,t-1}$, leaving to unemployment or out of the labor force during their careers $h^{lvr,UO}_{k,t-1}$, and the retirees from the labor market $h^{ent,rtr}_{k,t-1}$ sum to one. Then we plot the contributions of these groups to the marginal selection effect for each profession in the left panels of Figure XX.[33]

Second, we examine to what extent the differences in skills between incumbents and leavers reflect time-invariant endowments versus skill accumulation. We compute the skills that incumbents and leavers accumulated up until $t-1$ since they joined the sector $x_{i,t}$ periods ago in two different ways, using the estimated systematic accumulation ($s^{sty/lvr}_{k,i,t-1} - s^{sty/lvr}_{k,i,t-x_{i,t}} = \sum_{\tau=2}^{x_{i,t}} \sum_{a=1}^{A} I_{k,i,t-\tau} \cdot \mathbb{1}[\text{age}_{i,t-\tau} \in a] \cdot \hat{\gamma}_{k,k,a}$) and from the growth in their observed wages including idiosyncratic shocks ($s^{sty/lvr}_{k,i,t-1} - s^{sty/lvr}_{k,i,t-x_{i,t}} = w_{k,i,t-1} -$

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

$w_{k,i,t-x_{i,t}} + \hat{\pi}_{k,t-1} - \hat{\pi}_{k,t-x_{i,t}}$). We then plot the marginal selection component from Equation (15) that is due to differences at entry $\left(h^{lvr}_{k,t-1} - h^{ent}_{k,t}\right)\left(\mathrm{E}[s^{sty}_{k,i,t-x_{i,t}}] - \mathrm{E}[s^{lvr}_{k,i,t-x_{i,t}}]\right)$ versus the differences $\left(h^{lvr}_{k,t-1} - h^{ent}_{k,t}\right)\left(\mathrm{E}[s^{sty}_{k,i,t} - s^{sty}_{k,i,t-x_{i,t}}] - \mathrm{E}[s^{lvr}_{k,i,t} - s^{lvr}_{k,i,t-x_{i,t}}]\right)$ that are due to skill accumulation for each profession in the respective right panels of Figure XX.

Figure A7: Decomposing the marginal selection effect, accumulated

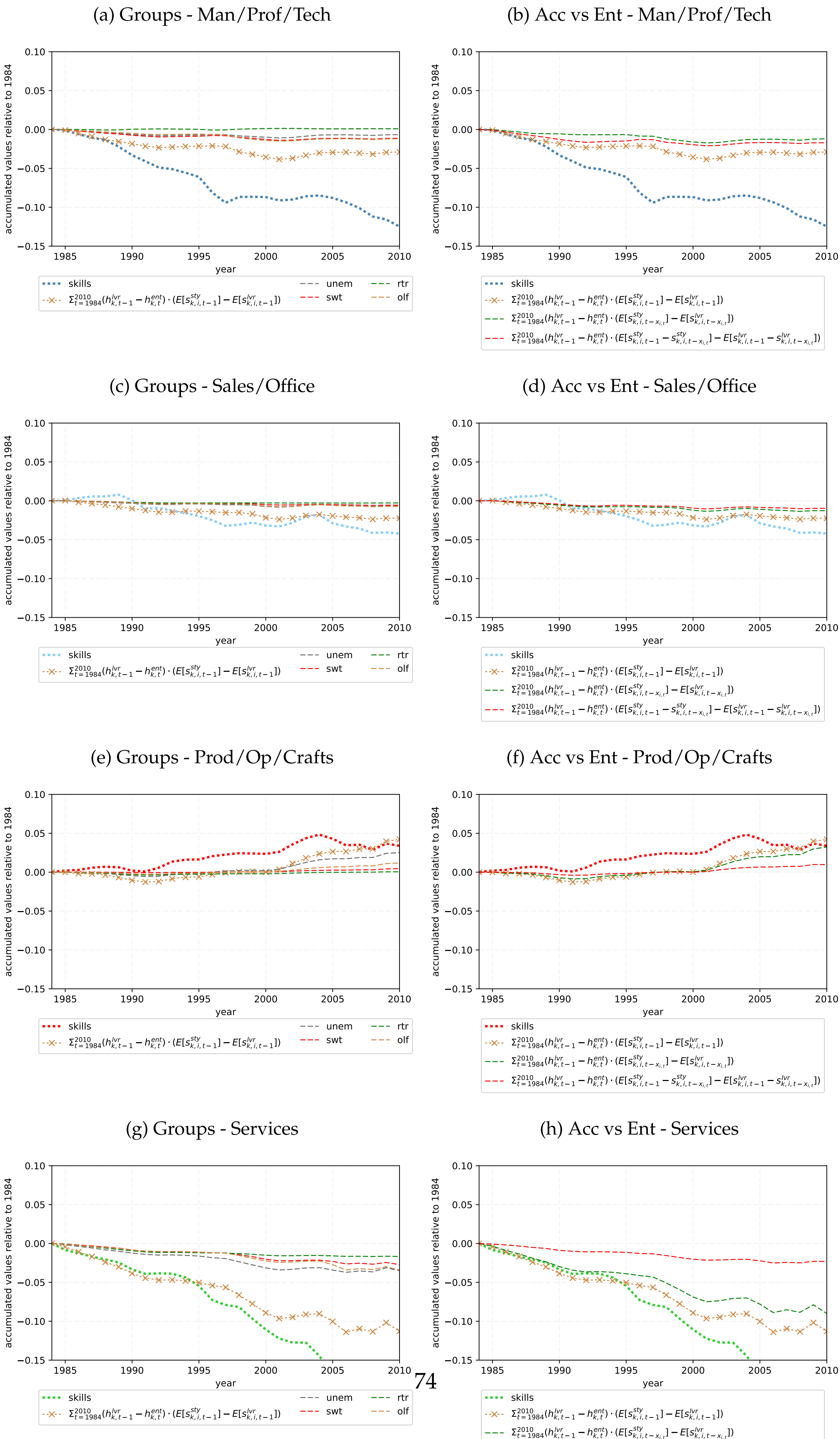


Figure A8: Relative to Production

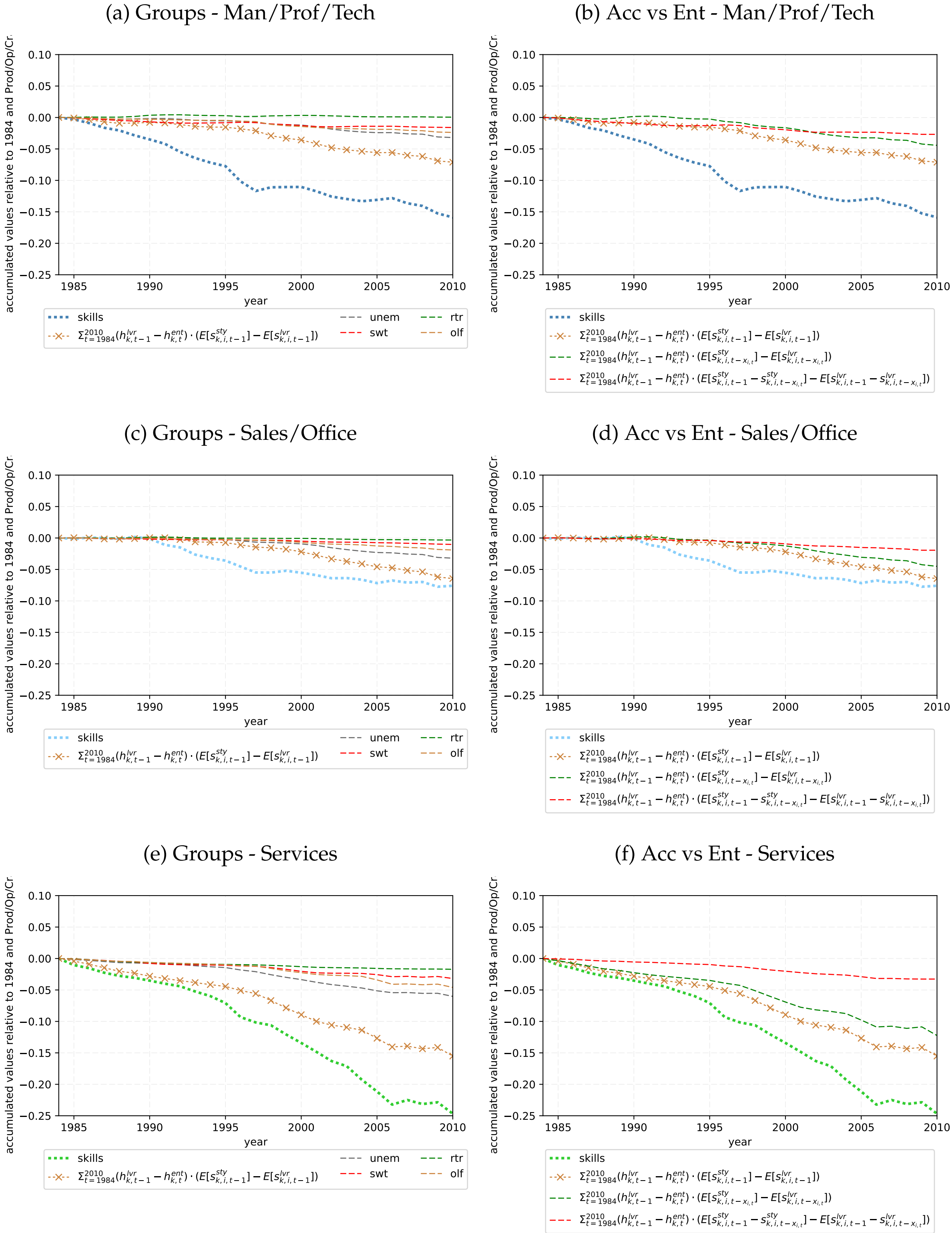
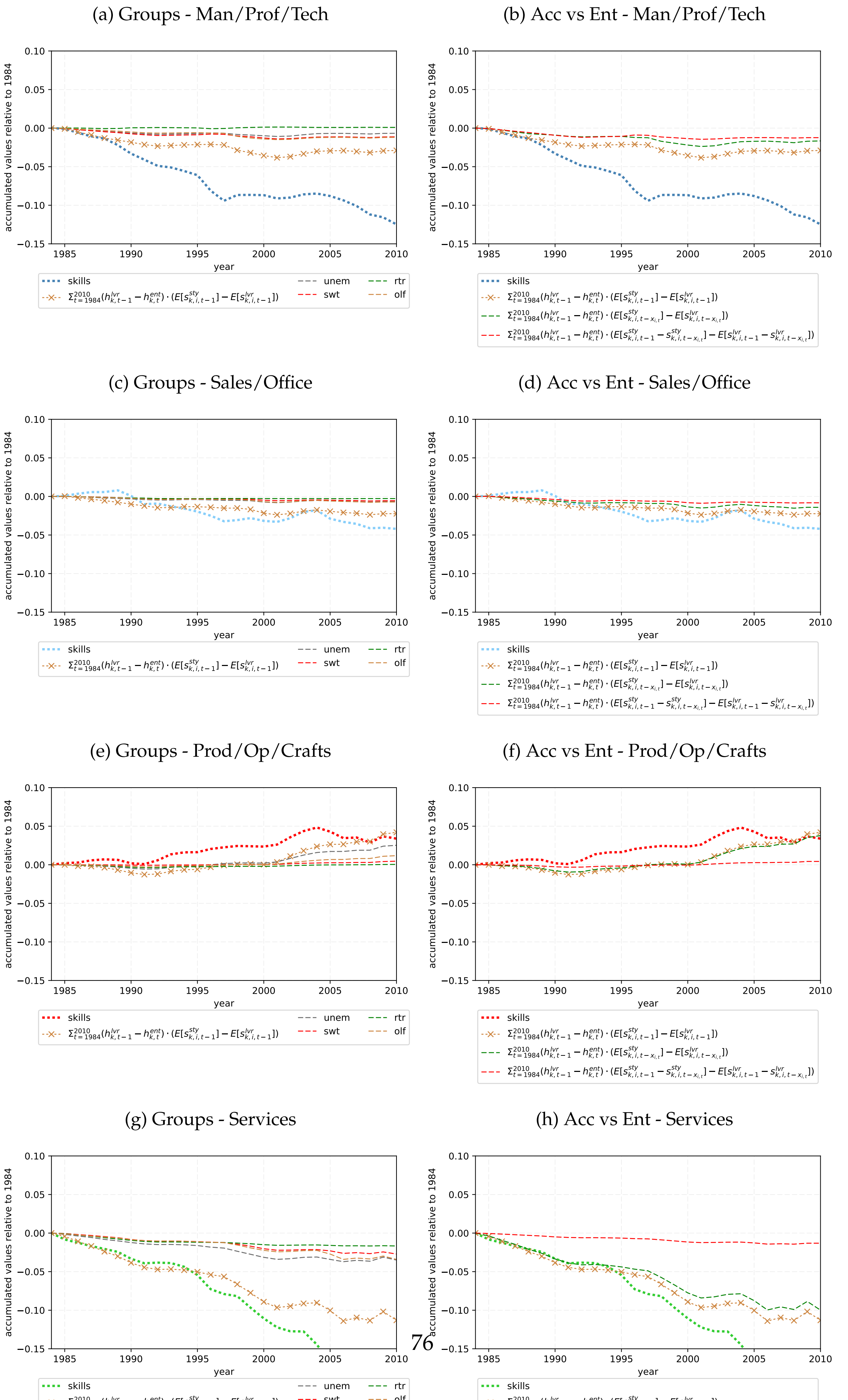


Figure A9: Decomposing the marginal selection effect, accumulated, from skill accumulation, i.e. without shocks



E Additional Figures and Tables

Table A2: Employment of labor market entrants by professions and cohort

	(1950, 1960]	(1960, 1970]	(1970, 1980]	(1980, 1990]
Man/Prof/Tech	0.11	0.08	0.08	0.09
Sales/Off	0.12	0.09	0.10	0.10
Prod/Op	0.58	0.53	0.37	0.32
Services	0.05	0.05	0.06	0.07
Unemp/OLF	0.14	0.26	0.39	0.42

Source: SIAB data, own calculations. The numbers show employment status at age 25. The unemployed / out of the labor force category is mainly made up by individuals not yet observed at this age in our data; the largest group here is presumably students in tertiary education (it lines up well with external numbers on this, too). *Legend:* Man/Prof/Tech: Managers, professionals, and technicians; Sales/Off: Sales and office; Prod/Op: Production workers, operators, and craftsmen; Unemp/OLF: Unemployed or out of the labor force.

Table A3: Percentages of Switchers and Stayers across categories

t t - 1	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	19.80	0.27	0.15	0.04
Sales/Office	0.30	11.15	0.17	0.04
Prod/Op/Crafts	0.34	0.25	45.68	0.31
Services	0.05	0.05	0.28	5.27
unem	0.24	0.20	1.03	0.27
olf	0.57	0.29	0.65	0.25

Table A4: Percentages of Switchers, conditional on State in $t-1$

t t - 1	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	95.23	1.28	0.72	0.21
Sales/Office	2.50	92.12	1.42	0.36
Prod/Op/Crafts	0.70	0.51	94.14	0.63
Services	0.86	0.84	4.60	86.22
unem	3.97	3.31	17.18	4.49
olf	8.74	4.48	10.05	3.89

Table A5: Wages of Switchers, before switching

t t - 1	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services	unem	olf
Mana/Prof/Tech	57229.3	50962.9	38729.6	36338.6	43614.8	43837.4
Sales/Office	50092.8	44724.7	30657.8	27869.8	33521.2	31121.8
Prod/Op/Crafts	39341.9	32421.2	34499.8	27032.3	26973.5	26444.5
Services	35175.1	28487.3	25787.4	32418.8	22203.2	21052.1

Table A6: Percentages of Switchers, conditional on State in t

t t - 1	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	92.96	2.18	0.31	0.69
Sales/Office	1.42	91.38	0.36	0.69
Prod/Op/Crafts	1.60	2.01	95.24	4.97
Services	0.25	0.42	0.59	85.22
unem	1.12	1.62	2.15	4.35
olf	2.66	2.38	1.36	4.07

Table A7: Wages of Switchers, after switching

t t - 1	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	58620.9	52718.2	39233.1	36945.0
Sales/Office	52619.2	45792.5	31474.0	28358.9
Prod/Op/Crafts	41224.7	33296.2	34846.9	27075.2
Services	37396.3	29933.6	27084.2	32825.1
unem	39169.1	30233.4	26001.7	21546.5
olf	43022.2	32044.5	25769.4	21962.0

Table A8: Percentages of Switchers and Stayers across categories

t t - 5	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	18.01	0.87	0.46	0.13
Sales/Office	1.00	9.63	0.50	0.13
Prod/Op/Crafts	1.48	0.88	42.98	1.01
Services	0.17	0.15	0.69	4.08
unem	0.44	0.34	1.57	0.41
olf	1.58	0.68	1.17	0.44

Table A9: Percentages of Switchers, conditional on State in $t - 5$

t t - 5	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	87.96	4.25	2.23	0.62
Sales/Office	8.32	79.71	4.16	1.07
Prod/Op/Crafts	2.95	1.76	85.71	2.02
Services	2.96	2.56	11.84	70.00
unem	7.78	5.97	27.78	7.27
olf	27.20	11.61	20.01	7.55

Table A10: Wages of Switchers, before switching

t t - 5	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services	unem	olf
Mana/Prof/Tech	55991.1	51033.5	39965.2	38132.5	46093.4	49468.1
Sales/Office	49563.8	43884.4	31640.2	30581.4	35973.2	35988.9
Prod/Op/Crafts	38299.1	33312.8	34475.8	29475.3	28949.5	28996.6
Services	34703.2	29770.8	28028.7	33550.4	24280.2	23687.8

Table A11: Percentages of Switchers, conditional on State in t

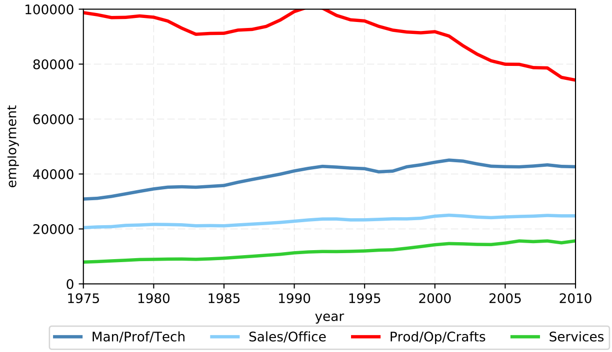
t t - 5	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	79.38	6.94	0.96	2.04
Sales/Office	4.43	76.75	1.06	2.09
Prod/Op/Crafts	6.51	7.05	90.74	16.34
Services	0.76	1.19	1.46	65.81
unem	1.94	2.69	3.31	6.62
olf	6.98	5.39	2.46	7.09

Table A12: Wages of Switchers, after switching

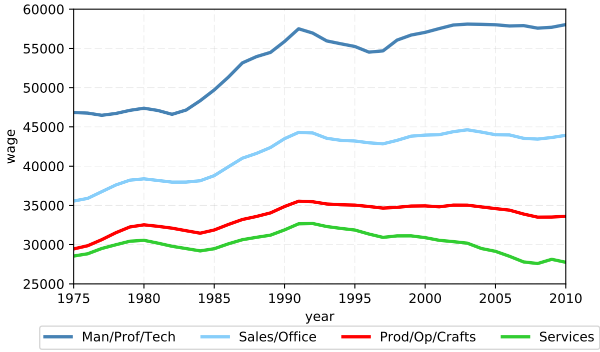
t t - 5	Mana/Prof/Tech	Sales/Office	Prod/Op/Crafts	Services
Mana/Prof/Tech	63504.5	58171.1	41291.0	40195.0
Sales/Office	59592.0	49105.3	33580.7	30804.8
Prod/Op/Crafts	45322.7	36618.8	36137.6	28948.3
Services	43416.9	34698.0	30891.2	35512.2
unem	42436.4	33136.5	27757.7	23370.7
olf	50583.4	39386.0	28787.7	26492.9

Figure A10: Further Evidence on Employment and Wage Trends

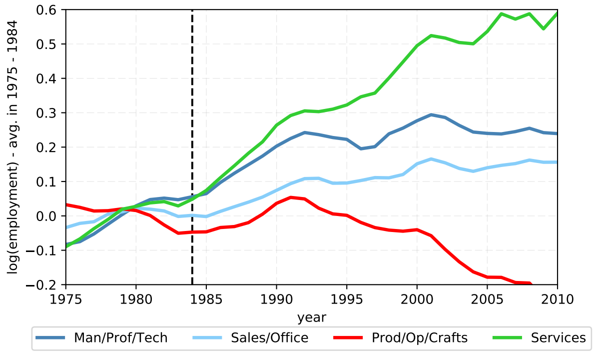
(a) Employment (not normalized)



(b) Average log Wages (not normalized)



(c) Employment (incl. pre-period)



(d) Average Log Wages (incl. pre-period)

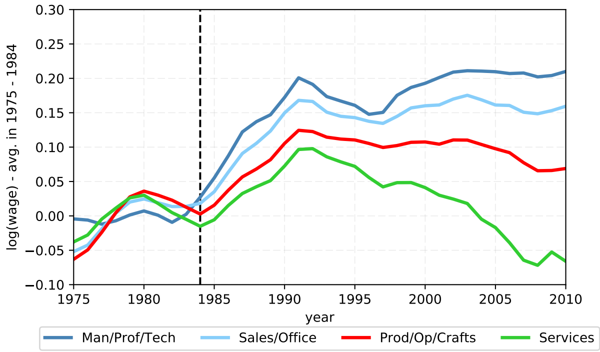
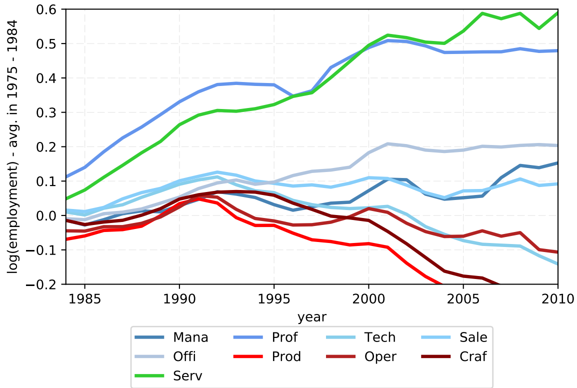
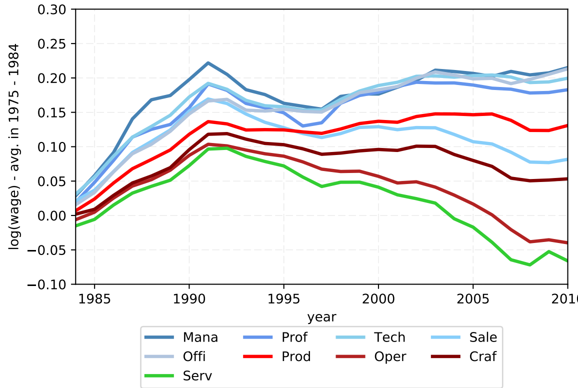


Figure A11: Additional Estimation Results

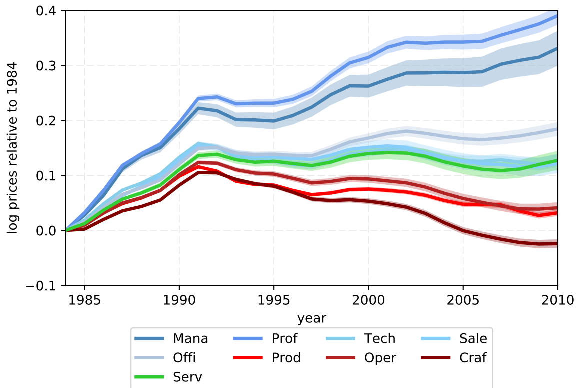
(a) Emploment (Nine Professions)



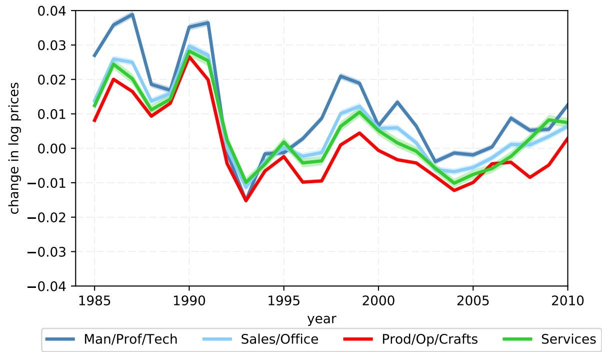
(b) Wages (Nine Professions)



(c) Task Prices (Nine Professions)

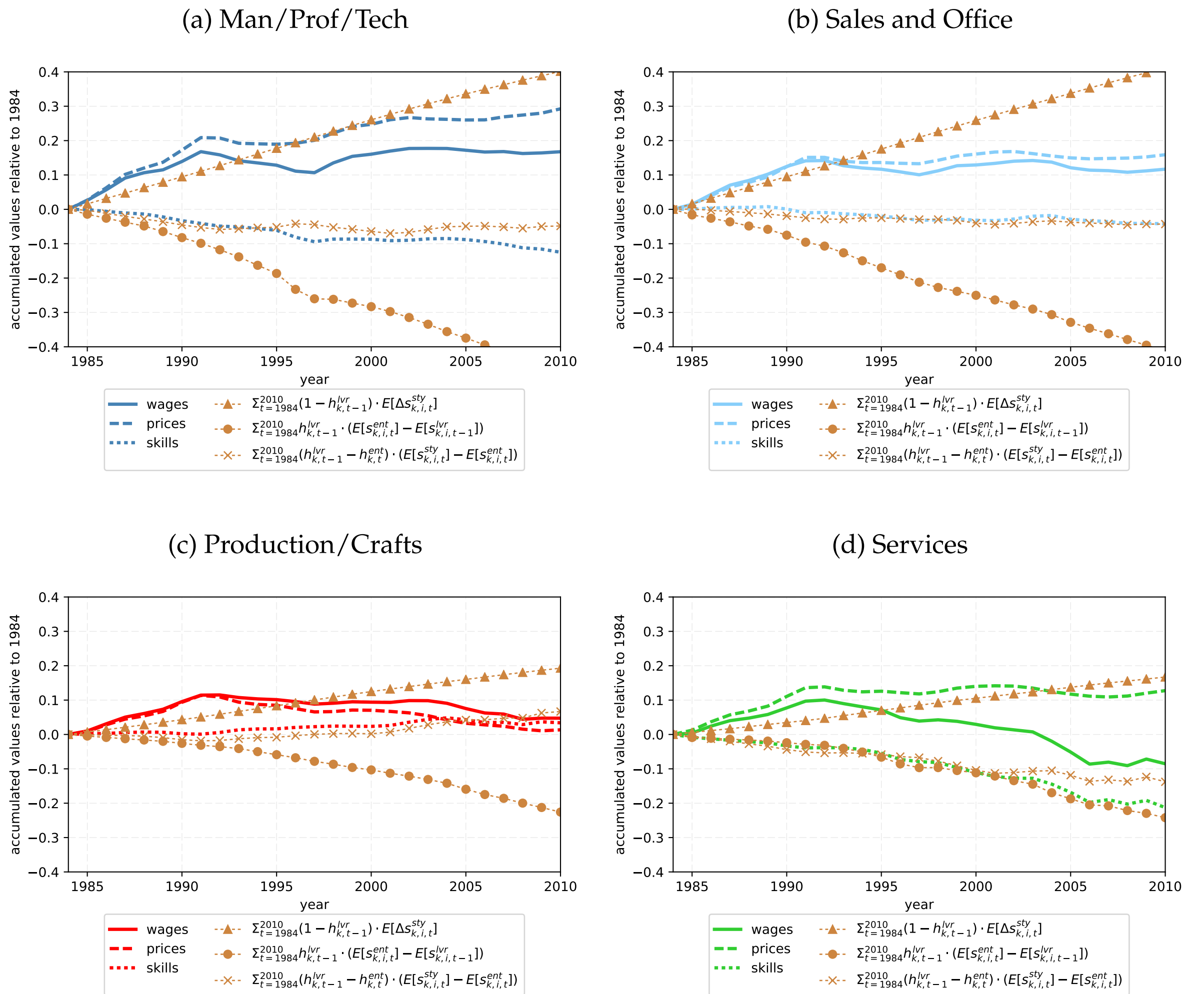


(d) Incremental Estimates



Notes:

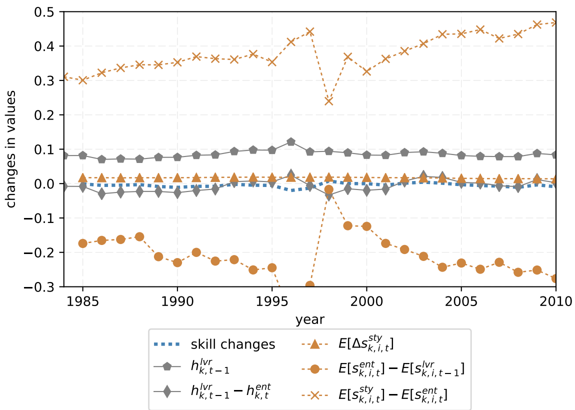
Figure A12: Average Wages, Task Prices, and Implied Skills in Professions. Decomposition of Skills into Accumulation, Churning, and Marginal Selection (All Absolute!)



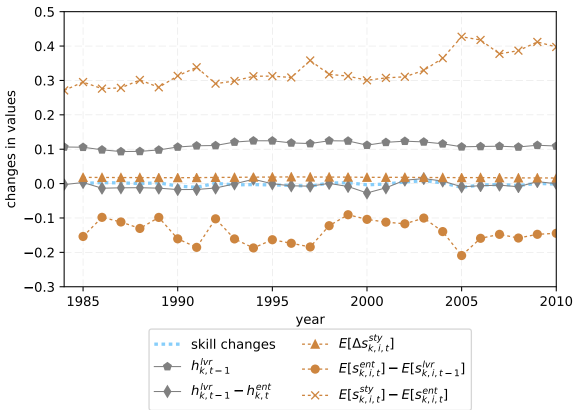
Notes: The colored main series of the Figure show average wages, cumulative task prices, and the difference between two (i.e. the skill composition) of in the four professions over time. The brown dashed and dotted series show Equation (15)'s further decomposition of professions' skill selection into effects due to accumulation, churning, and marginal selection.

Figure A13: Elements of Decomposition (15) Incrementally

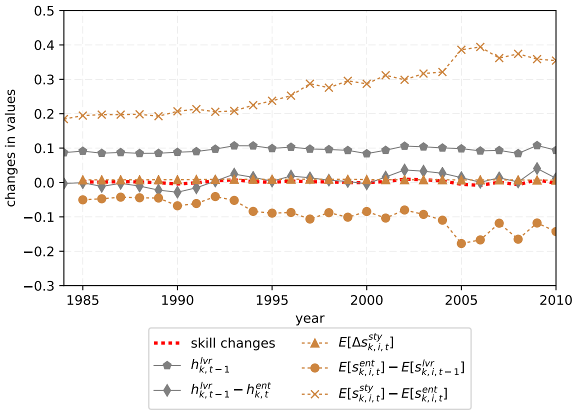
(a) Man/Prof/Tech



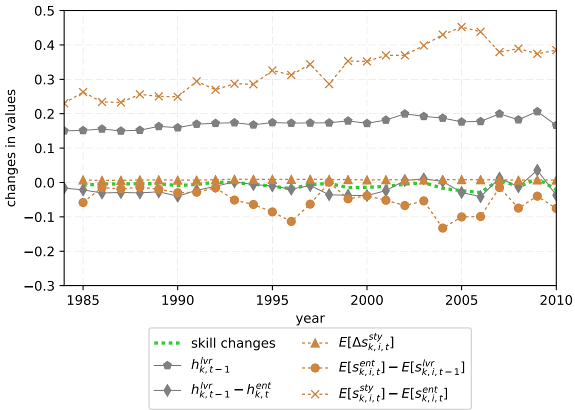
(b) Sales and Office



(c) Production and Crafts



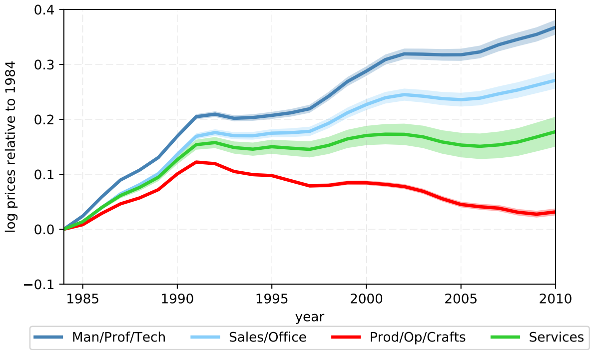
(d) Services



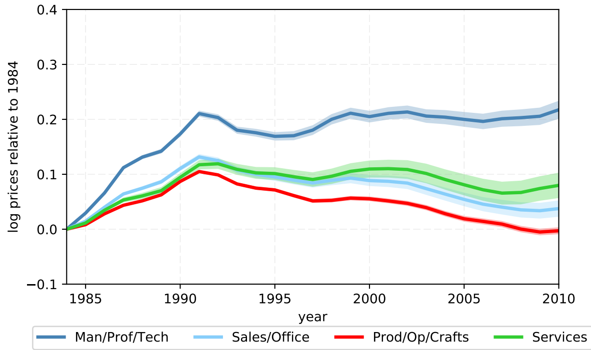
Notes: TBW

Figure A14: Robustness: Task Prices for Different Age and Demographic Groups

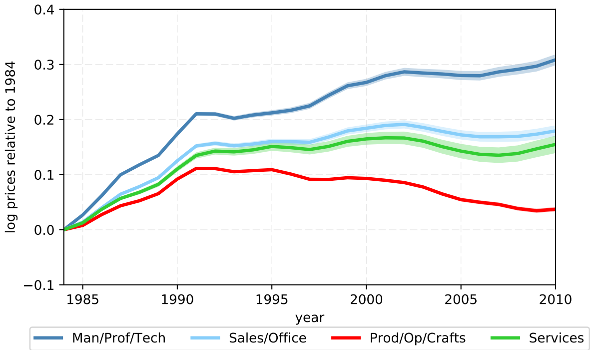
(a) Ages 25–39



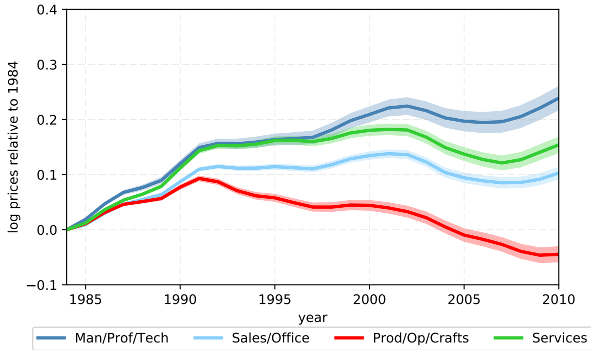
(b) Ages 40–54



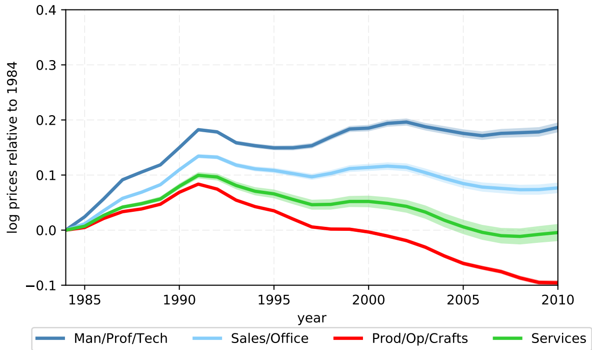
(c) With Easterners and foreigners



(d) Women Only



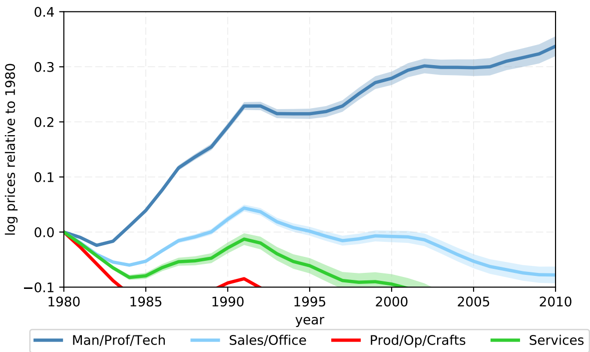
(e) Ages 21–60



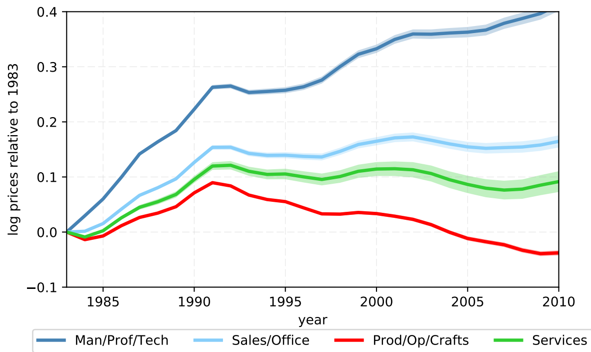
Notes: TBW

Figure A15: Robustness: Task Prices with different base periods

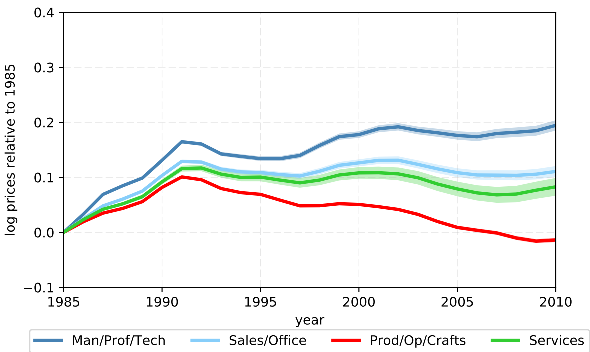
(a) 1980



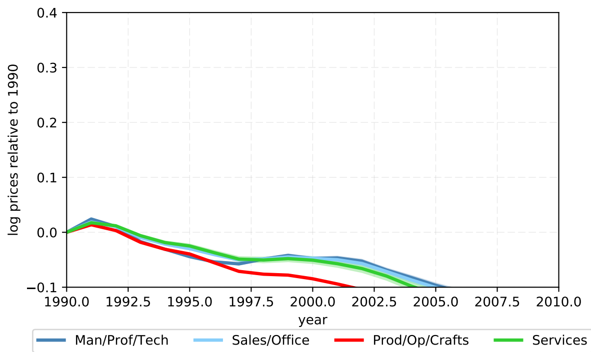
(b) 1983



(c) 1985



(d) 1990



Notes: TBW

F Dataset Construction

For the empirical analysis, we make use of German social security records - the SIAB Scientific Use File, provided by the IAB[34]. See Antoni et al. (2016) 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 and individuals performing military service. Most notably, it contains an individual's full employment history, the occupation, wage, and some sociodemographics. 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.) as most other studies aggregate all the information from various spells within a year. For example, they add up all the earnings from multiple employment spells. As our focus is on occupations, this is impossible to do as one can not aggregate multiple categorical occupation information. Nevertheless, the amount of *full time* workers with more than one spell a year is negligible and so of minor concern. However, as some spells last for less than 365/366 days within a year, we weight all observations by their spell duration within a year, i.e. an employer working 120 days in t receives $\omega_{i,t} = 120$ 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 we aggregate the nine professions mentioned in the table into the four professions:

1. Managers/Professionals/Technicians
2. Sales/Office
3. Production/Operators/Craftsmen
4. Services

The contained education variable is imputed as 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 degree). The age bins used for estimating the skill accumulation parameters are $[25, 34]$, $[35, 44]$, $[45, 54]$.

[34]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.

Wage Imputations: Despite being accurately measured as the employer can be punished for incorrect reports of the wage, the contained wage variable has two major drawbacks for our analysis. At first, wages are top coded amounting in 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 that, 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[35]. 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[36]. 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 as 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 as 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 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 Managers/Professionals/Technicians group aged $[45, 54]$ increases from previous 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 Managers/Professionals/Technicians fall between 1975 and 1983, especially for old 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.

[35]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.

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

Sample Selection: The main dataset is restricted to full time working 25 to 54 year olds. 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 employment spells for East-Germany as well as foreign workers[37]. After that, we am left with 827,619 persons and 9,744,558 person times year combinations. From that, 351,673 persons and 3,167,627 person times year combinations are women so that 475,946 individuals and 6,576,931 person times year combinations are men which are used for the price estimations.

[37] A person is classified as foreign, if he is *never* indicated as being German.

Managers	Entrepreneurs, managing directors, divisional managers
	Management consultants, organisors until chartered accountants, tax advisers
	Members of Parliament, Ministers, elected officials until association leaders, officials
Professionals	Architects, civil engineers
	Bank specialists until building society specialists
	Chemists, chemical engineers until physicists, physics engineers, mathematicians
	Data processing specialists
	Economic and social scientists, statisticians until scientists n.e.c
	Electrical engineers
	Health insurance specialists (not social security) until life, property insurance specialists
	Home wardens, social work teachers
	Journalists until librarians, archivists, museum specialists
	Mechanical, motor engineers
	Music teachers, n.e.c. until other teachers
	Musicians until scenery/sign painters
	Physicians until Pharmacists
	Social workers, care workers until religious care helpers
	University teachers, lecturers at higher technical schools and academies until technical, vocational, factory instructors
	VVermessungingenieure bis sonstige Ingenieure
Technicians	Biological specialists until physical and mathematical specialists
	Chemical laboratory assistants until photo laboratory assistants
	Electrical engineering technicians until building technicians
	Foremen, master mechanics
	Measurement technicians until remaining manufacturing technicians
	Mechanical engineering technicians
	Other technicians
	Technical draughtspersons
Crafspeople	Agricultural machinery repairers until precision mechanics
	Bakery goods makers until confectioners (pastry)
	Bricklayers until concrete workers
	Butchers until fish processing operatives
	Carpenters
	Carpenters until scaffolders
	Cutters until textile finishers
	Dental technicians until doll makers, model makers, taxidermists
	Electrical fitters, mechanics
	Gardeners, garden workers until forest workers, forest cultivators
	Motor vehicle repairers
	Other mechanics until watch-, clockmakers
	Plumbers
	Roofers
	Room equippers until other wood and sports equipment makers
	Stucco workers, plasterers, rough casters until insulators, proofers
	Telecommunications mechanics, craftsmen until radio, sound equipment mechanics
	Tile setters until screed, terrazzo layers
	Toolmakers until precious metal smiths
Sales personnel	Commercial agents, travellers until mobile traders
	Forwarding business dealers
	Publishing house dealers, booksellers until service-station attendants
	Salespersons
	Tourism specialists until cash collectors, cashiers, ticket sellers, inspectors
	Wholesale and retail trade buyers, buyers
Office workers	Cost accountants, valuers until accountants
	Office auxiliary workers
	Office specialists
	Stenographers, shorthand-typists, typists until data typists
Production workers	Building labourer, general until other building labourers, building assistants, n.e.c.
	Ceramics workers until glass processors, glass finishers
	Chemical laboratory workers until vulcanisers
	Chemical plant operatives
	Drillers until borers
	Electrical appliance fitters
	Electrical appliance, electrical parts assemblers
	Engine fitters
	Farmers until animal keepers and related occupations
	Generator machinists until construction machine attendants
	Goods examiners, sorters, n.e.c.
	Goods painters, lacquerers until ceramics/glass painters
	Iron, metal producers, melters until semi-finished product fettlers and other mould casting occupations
	Locksmiths, not specified until sheet metal, plastics fitters
	Machine attendants, machinists' helpers until machine setters (no further specification)
	Metal grinders until other metal-cutting occupations
	Metal polishers until metal bonders and other metal connectors
	Metal workers (no further specification)
	Miners until shaped brick/concrete block makers
	Other assemblers
	Packagers, goods receivers, despatchers
	Painters, lacquerers (construction)
	Paper, cellulose makers until other paper products makers
	Paviors until road makers
	Plant fitters, maintenance fitters until steel structure fitters, metal shipbuilders
	Plastics processors
	Sheet metal pressers, drawers, stampers until other metal moulders (non-cutting deformation)
	Sheet metal workers
	Special printers, screeners until printer's assistants
	Spinners, fibre preparers until skin processing operatives
	Steel smiths until pipe, tubing fitters
	Tracklayers until other civil engineering workers
	Turners
	Type setters, compositors until printers (flat, gravure)
	Welders, oxy-acetylene cutters
	Wine coopers until sugar, sweets, ice-cream makers
	Wood preparers until basket and wicker products makers
Operators, laborers	Motor vehicle drivers
	Navigating ships officers until air transport occupations
	Post masters until telephonists
	Railway engine drivers until street attendants
	Stowers, furniture packers until stores/transport workers

Continued on next page

	Transportation equipment drivers
	Warehouse managers, warehousemen
Service personnel	Artistic and assisting occupations (stage, video and audio) until performers, professional sportsmen, auxiliary artistic occupations
	Assistants (no further specification)
	Cashiers
	Cooks until ready-to-serve meals, fruit, vegetable preservers, preparers
	Dietary assistants, pharmaceutical assistants until medical laboratory assistants
	Doormen, caretakers until domestic and non-domestic servants
	Factory guards, detectives until watchmen, custodians
	Hairdressers until other body care occupations
	Household cleaners until glass, buildings cleaners
	Housekeeping managers until employees by household cheque procedure
	Laundry workers, pressers until textile cleaners, dyers and dry cleaners
	Medical receptionists
	Non-medical practitioners until masseurs, physiotherapists and related occupations
	Nursery teachers, child nurses
	Nurses, midwives
	Nursing assistants
	Others attending on guests
	Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers until waiters, stewards
	Soldiers, border guards, police officers until judicial enforcers
	Street cleaners, refuse disposers until machinery, container cleaners and related occupations