The Polarization of Skill Prices in Germany, 1985 – 2010*

Preliminary, incomplete and with errors.

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Abstract

We propose a new method to estimate changing skill prices and skill accumulation across multiple sectors. The method exploits workers' wage growth in panel data, allowing for an unrestricted multidimensional distribution of skills and endogenous switching due to skill shocks. We apply our method to high-quality German administrative records and find that the skill prices for work in abstract as well as manual non-routine professions increased substantially compared to routine professions. Average wages in the (manual non-routine) services profession dropped despite rising skill prices for two reasons: (1) extraordinary high and increasing turnover in the profession, which prevented skill accumulation, and (2) a negative and deteriorating selection of skills entering the profession. Overall, our results are consistent with a pervasive impact of routine-biased technical change on the German wage structure, and with increasingly precarious work biographies driving inequality at the bottom of the wage distribution.

Keywords: Skill Prices; Tasks; Multisector Roy Model; Wage Inequality; Routine-Biased Technical Change; Panel Data; German Administrative Records

JEL codes: J23, J24, J31

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1 Introduction

From the mid 80's onwards, employment in Germany has polarized strongly. Occupations from the middle of the skill and wage distribution reported large employment drops whereas occupations at the margins achieved employment gains (Dustmann, Ludsteck, and Schönberg, 2009). According to the seminal work of Autor, Levy, and Murnane (2003), middling occupations are characterized by a comparatively large amount of routine tasks which workers perform. In contrast, high skill occupations mainly consist of non-routine analytical or interactive tasks and low skill occupations can be described by a mixture of interactive and manual tasks. Therefore, the work performed in middling occupations is much more vulnerable to be replaced by automation technologies or to be offshored than the work done in the occupations at the fringes.

If the replacement of routine tasks by technology or foreign labor not only affects the employment channel but also the wage channel, we would suspect that the wage distribution also polarized over time resulting in wage declines for middling and wage gains for low and high skilled occupations (Autor, Katz, and Kearney, 2006). Admittedly, wage inequality in Germany increased substantially over the last couple of decades (Card, Heining, and Kline, 2013; Dustmann, Ludsteck, and Schönberg, 2009) but this happened monotonically upwards the skill distribution as low skill (service) occupations had even stronger wage losses than middling (producing) occupations and high skill (managerial, clerical) occupations reported wage gains. A polarization of the wage distribution was only observed for the US in the 90's (Acemoglu and Autor, 2011).

Nevertheless, in this paper, we argue that pure mean wage changes within skill bins are a bad indicator to qunatify the impact of technological change on inequality and polarization. Wage changes for an individual worker are the result of shifts of the worker's skills and the prices paid for those. Hence, mean wage changes within certain occupational skill groups contain a price and a composition effect. If the price paid for producing professions falls because of new automation technologies or offshoring, this does not necessarily imply occupational wage polarization as, for example, production workers may transition into occupations at a different part of the skill distribution and thereby alter the skill composition of their new and old occupation (Autor, Katz, and Kearney, 2006). Such a movement could, for instance, lead to falling mean wages of service occupations if low skilled production workers leave their former profession and start a new career in the service sector. Although, the relative price for services may have risen over time, the evolution of the mean wage of service occupations is ambiguous. If we want to quantify the impact of automation and offshoring on the wage distribution, it is therefore necessary to disentangle price and composition effects as a possible polarization of skill prices could be offset by composition effects through selection.

To do so, we estimate the equilibrium price paid for working in professions associated with high intensities of routine tasks compared to professions mainly associated with analytical, interactive, and manual tasks. We therefore develop a novel estimation method which exploits the interplay between workers' sorting into professions and their wage growth in panel data. The method has the advantages that it makes minimal assumptions about the distribution of workers' skills and that it can be implemented in simple linear wage regressions[1].

In addition, we are also able to flexibly account for how individuals acquire skills over their working lives, extending the work of Yamaguchi (2012). Our estimation flexibly allows that workers acquire skills "on the job". Within each profession they perform analytical, interactive, routine or manual tasks. By performing those tasks, they build up their profession specific skills. We allow the task content to differ on a fine grid of 120 occupations as Production workers may perform more routine tasks than Sales and Office workers whereas Managers, Professionals and Technicians demand for more analytical tasks.

To estimate skills and prices paid for those, we rely on the identifying assumption that, conditional on the evolution of skills, workers only change from a routine intensive profession to, say, an analytical intensive one if the wage in the latter is higher than in the former.

We combine two datasets for our empirical analysis. As we model skills to be acquired on the job by performing tasks, we make use of a unique Germany survey dataset, the Qualification and Career Survey (QCS), to measure the intensity with which tasks are performed in each occupation. Second, we employ the Sample of Integrated Labor Market Biographies (SIAB). This administrative dataset has information on both, workers' wage growth and their sorting into professions over time. It therefore allows us to estimate the evolution of workers' profession specific skills over the life-cycle and to elicit the market prices paid for those. We combine the datasets by using occupational identifiers which we can construct for both datasets.

We use our skill price estimates to decompose the evolution of mean wages within professions into the effects of a changing skill composition and the prices paid for those skills. In addition, the estimated prices also allow us answering the question whether routine-biased technological change was important in the German context and to quantify its impact on the increase in inequality. Finally, possessing information about employment and profession price changes, we are able to compute labor supply elasticities with respect to different professions. These labor supply elasticities are important variables for policy makers, because they indicate to

[1]The approach is inspired by the recent papers of Böhm (2015), Cortes (2016) and Gottschalk, Green, and Sand (2015).

what extent workers can switch professions in response to different market prices and thus adjust to a shifting labor demand structure in the economy.

The paper is structured as follows. Section 2 presents the self selection model as well as a method to estimate it's parameters, the market skill prices and parameters which govern the evolution of skills. Section 3 describes the datasets we employ. Evidence on the claims about the German employment and wage structure which were made above is presented in section 4. The estimation results are depicted in section 5. Section 6 discusses the findings and concludes.

2 Model

We assume that there are $k = 1, \ldots, K$ distinct occupational groups or sectors which we simply refer to as "professions"[2]. Each worker is employed in such a profession k and is endowed with sector specific log skills $s_{k,i,t}$ for which he receives a log wage $w_{i,t} = w_{k,i,t} = \pi_{k,t} + s_{k,i,t}$. The returns to profession skills $\pi_{k,t}$ are market prices which may vary offer time and which changes we want to estimate.

Skills are acquired through "learning on the job" by performing tasks $x_{k,i,t}$. In each occupation, all the workers conduct the same amount of analytical, interactive, routine or manual tasks and so accumulate skills. Skills of Production and Operate workers may mainly be accomplished by performing routine tasks; whereas skills of Managers, Professionals and Technicians may mostly be collected by executing analytical and interactive tasks[3].

A worker chooses to work in the profession k in which he has a comparative advantage. Therefore, he self selects into a certain profession and ends up with a wage:

$$w_{i,t} = \max\{\pi_{1,t} + s_{1,i,t}, \ldots, \pi_{K,t} + s_{K,i,t}\} \tag{1}$$

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

[2] The five groups used for the empirical analysis are inspired by the grouping of Acemoglu and Autor (2011). To construct the groups, we map the 120 occupations contained in the SIAB to be either Managers/Professionals/Technicians, Sales/Office, Production/Operate or Services. See section A.1 for the mapping.

[3] See table 4 for our mean task intensity estimates for each profession.

$$
dw_{i,t} = \begin{cases} dw_{1,i,t} = d(\pi_{1,t} + s_{1,i,t}) & \text{if } I_{1,i,t} = 1 \\ \quad \vdots & \\ dw_{k,i,t} = d(\pi_{K,t} + s_{K,i,t}) & \text{if } I_{K,i,t} = 1. \end{cases} \tag{2}
$$

where $I_{k,i,t} = 1[\max_{j=1,\ldots,K}\{w_{j,i,t}\} = w_{k,i,t}] = 1[w_{k,i,t} \geq w_{j,i,t} \, \forall j \neq k] = 1[w_{k,i,t} - w_{j,i,t} \geq 0 \, \forall j \neq k]$ is the profession choice indicator. We can rewrite this to:

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

Define profession j to be the reference profession to which we estimate relative profession prices and $\tilde{w}_{k,i,t} = w_{k,i,t} - w_{j,i,t}$. Then we can rewrite 3 to:

$$
dw_{i,t} = dw_{j,i,t} + \sum_{k=1, k \neq j}^{K} I_{k,i,t} d\tilde{w}_{k,i,t} \tag{4}
$$

To get from marginal changes to absolute ones, hold constant $\tilde{w}_{k,i,t} \forall \; k \neq j$ at first. Then integrating 4 with respect to the baseline wage $\tilde{w}_{j,i,t}$ gives:

$$
w_{i,t|w_{j,i,t}, \tilde{w}_{k,i,t} \forall \; k \neq j} - w_{i,t|w_{j,i,t-1}, \tilde{w}_{k,i,t} \forall \; k \neq j} = \Delta w_{j,i,t} \tag{5}
$$

Now hold constant $\tilde{w}_{j,i,t}$ instead and integrate with respect to $\tilde{w}_{l,i,t}$. Then, similarly, we receive:

(6)

$$
\forall \; l \in \{1, \ldots, K\}, \; l \neq j : w_{i,t|w_{j,i,t}, \tilde{w}_{l,i,t}, \tilde{w}_{k,i,t} \forall \; k \neq j,l} - w_{i,t|w_{j,i,t}, \tilde{w}_{l,i,t-1}, \tilde{w}_{k,i,t} \forall \; k \neq j,l} = \int_{w_{l,i,t} - w_{j,i,t}}^{w_{l,i,t-1} - w_{j,i,t-1}} I_{l,i,t} d\tilde{w}_{l,i,t}
$$

If we sum up the one equation defined by 5 and the $K-1$ equations defined by 6, we get:

$$
\Delta w_{i,t} = \Delta w_{j,i,t} + \sum_{k=1, k \neq j}^{K} \int_{\tilde{w}_{k,i,t-1}}^{\tilde{w}_{k,i,t}} I_{k,i,\tau} d\tilde{w}_{k,i,\tau} \tag{7}
$$

To make this estimable, we linearly approximate 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:

$$I_{k,i,\tau} \approx I_{k,i,t-1} + \frac{I_{k,i,t} - I_{k,i,t-1}}{\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}}(\tilde{w}_{k,i,\tau} - \tilde{w}_{k,i,t-1}) \tag{8}$$

After plugging this approximation into 7, we end up with a very intuitive result[4]:

$$\begin{aligned} \Delta w_{i,t} &= \Delta\pi_{j,t} + \Delta s_{j,i,t} + \sum_{k=1,k\neq j}^{K} \bar{I}_{k,i,t}(\Delta\pi_{k,t} - \Delta\pi_{j,t}) + \bar{I}_{k,i,t}(\Delta s_{k,i,t} - \Delta s_{j,i,t}) \\ &= \sum_{k=1}^{K} \Delta\pi_{k,t}\bar{I}_{k,i,t} + \sum_{k=1}^{K} \Delta s_{k,i,t}\bar{I}_{k,i,t} \end{aligned} \tag{9}$$

where $\bar{I}_{k,i,t} \equiv \frac{I_{k,i,t}+I_{k,i,t-1}}{2}$.

Due to the approximation of the integral, the wage change for i from $t-1$ to t can be decomposed as follows: If i stayed in profession k, he gets a potential wage gain $\Delta w_{k,i,t}$ from that profession. If i switched, he gets half of the potential wage gain from the origin and half from the destination profession. 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.

To estimate 9, we need data on log wage changes $\Delta w_{i,t}$, moves from to profession to profession from which we construct $\bar{I}_{k,i,t}$ and the change in skills. As we don't have data on skill changes, we make several competing assumptions to model $\Delta s_{k,i,t}$.

2.1 Time-Constant Skills

If the workers profession specific skills do not change over time[5], i.e. $\Delta s_{k,i,t} = 0$, then $\beta_{k,t} = \Delta\pi_{k,t}$ identifies the changing profession prices in a simple linear wage regression of the log change in wages on profession choice indicators:

[4] See appendix A.3 for the derivation.

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

$$\Delta w_{i,t} = \sum_{k=1}^{K} \beta_{k,t} \bar{I}_{k,i,t} \tag{10}$$

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.

2.2 Time-Varying Skills Without Depreciation

If $s_{k,i,t}$ is not time constant, then endogenous switches can occur. To account for this, we model the evolution of skills like Yamaguchi (2012) as "learning by doing" on the job. For simplicity we do not allow for depreciating skills at first.

Workers accumulate profession specific skills by performing analytical, interactive, routine or manual tasks. In each occupation, a different set of tasks is required at work. We estimate the task contents of professions by using the survey data described in section 3.2. The resulting mean estimates for each profession for can be found in table 4.

Let the task content which worker i of age group a performs at time $t-1$ be described by $x_{i,t-1} = (\text{analytical}, \text{interactive}, \text{routine}, \text{manual})_{i,t-1}$. Analytical tasks are transformed into profession skills with factor $\gamma_{k,a}^{\text{ana}}$ which we estimate in the data and likewise for the other tasks with factors $\gamma_{k,a}^{\text{int}}, \gamma_{k,a}^{\text{rout}}, \gamma_{k,a}^{\text{man}}$. In addition, we also include a constant $\gamma_{k,a}^{\text{con}}$ in the skill formation process to allow some professions to have higher accumulation paths than others. Hence, the change in profession specific skills is modeled as:

$$\Delta s_{k,i,t} = \gamma_{k,a} \cdot \begin{pmatrix} 1 & x_{i,t-1} \end{pmatrix}^{\mathrm{T}} \cdot \mathbb{I}[\text{age}_{i,t-1} \in a] + v_{k,i,t} \tag{11}$$

In this notation $\gamma_{k,a}$ is a five dimensional parameter vector which we estimate. As the speed of skill accumulation probably declines with age, we make the transformation age specific. The age groups we use are 21-30, 31-40 and 41-50 year olds. To be able to identify prices and skills, we have to rely on the assumption that the skill accumulation process is constant over time, i.e. $\gamma_{k,a}$ is time independent. In addition, we assume that the prices changed at an equal speed in the pre-polarization era (1975-1984):

$$\Delta\pi_{k,t} = \bar{\pi} \quad \text{if } t \leq 1984,\ k = 1, \ldots, K \tag{12}$$

We consider this assumption to be valid as we do not observe much employment polarization or huge differences in wage gains between the professions in this period as shown by figure 1 and figures 2 and 5.

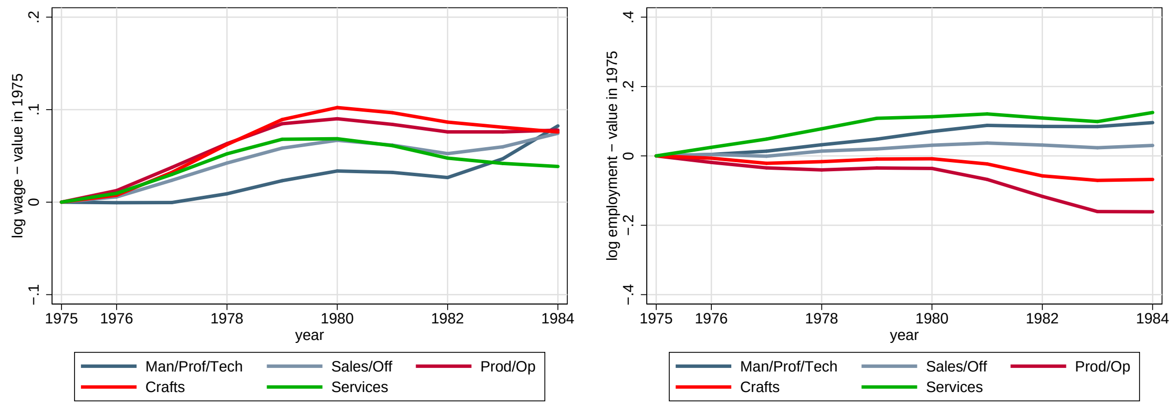


Figure 1: Wages and employment in the pre-polarization era (the wage break in 1983 is not yet fully corrected which is why the wages of Managers/Professionals/Technicians behave so strangely).

We so arrive at the wage equation:

$$\Delta w_{i,t} = \sum_{k=1}^{K} \beta_{k,t} \bar{I}_{k,i,t} + \sum_{k=1}^{K} \gamma_{k,a} \cdot \begin{pmatrix} 1 & x_{i,t-1} \end{pmatrix}^{\mathrm{T}} \cdot \mathbb{I}[\text{age}_{i,t-1} \in a] \bar{I}_{k,i,t} + u_{i,t} \tag{13}$$

Again, the price changes are identified by $\Delta\pi_{k,t} = \beta_{k,t}$ in simple regressions[6].

2.3 Time-Varying Skills With Depreciation

In a next step, we allow for depreciating skills. We model the evolution of skills to depend on the previous state:

$$\Delta s_{k,i,t} = (d_k - 1) s_{k,i,t-1} + a_k \cdot x_{i,t-1} + h_k \cdot G_{i,t-1} + v_{k,i,t} \tag{14}$$

[6]Nevertheless, we have an endogeneity bias as the error term $u_{i,t} = v_{j,i,t} + \sum_{k=1,k\neq j}^{K} (v_{k,i,t} - v_{j,i,t}) \bar{I}_{k,i,t}$ is correlated with the regressor $\bar{I}_{k,i,t}$ if $v_{k,i,t} \neq v_{j,i,t} \forall k \neq j$ (Cortes (2016, p. 68) makes this assumption).

The model will be estimated with Maximum-Likelihood. For initial conditions for s_0, we will use finer grained task measures and various sociodemographic characteristics. d_k reflects the depreciation of skills in profession k. In the same spirit as Yamaguchi (2012), we allow the rate to differ across tasks. a_k measures "learning by doing". If $d_k > 0$, then skills depreciate which agents can only overcome by performing tasks measured by $x_{i,t-1}$. We condition the analysis on sociodemographic groups contained in $G_{i,t-1}$.

3 Data

The empirical analysis makes use of two German datasets. To map occupations into tasks, we employ the Qualification and Career Survey (QCS). This is a survey of employees carried out six times in the years 1979–2012 by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung; BIBB) and the Research Institute of the Federal Employment Service (Institut für Arbeitsmarkt-und Berufsforschung; IAB). For our main analysis of wage growth and occupational choice we rely on social security records, the SIAB, provided by the IAB as well.

3.1 SIAB

The SIAB is a 2% random sample of administrative social security records from 1975 to 2010. It is representative for 80% of the German workforce but excludes the self-employed, civil servants and individuals performing their military service. The SIAB contains an individual's full employment history, the occupation, wage, and some sociodemographics. For a more detailed description see Dustmann, Ludsteck, and Schönberg (2009). We prepared the data, to the greatest extend, as they did.

At first, spells which are most likely to be missing because of data problems are imputed as described in Drews, Groll, and Jacobebbinghaus (2007). After that, the education variable is imputed as it contains a lot of inconsistencies and missing values as described in Fitzenberger, Osikominu, and Völter (2006). We generate an education variable with three possible outcomes: low (without postsecondary education), medium (apprenticeship or Abitur) and high (university degree).

Then the spell structure is transformed into a panel structure. The longest spell for a person within a year is used as the observation for this year. All of the results are weighted by the spell duration we observe.

Afterwards, the dataset is restricted to full-time working, West–German men with age between 21 and 50. We restrict the dataset in this way as we want to avoid selection problems. Women often have long career breaks due to birth of children which come along with lower wages and sorting into different occupations than before the child was born. Workers older than 50 begin to select into retirement.

We also have to drop observations where no information on the occupation is available and where the daily wage is below than the left censoring limit as this is assumed to be unreasonable as described in Büttner and Rässler (2008). Since the definition of a wage changed from 1983 to 1984, we observe a break in the data. Before 1984 wages did not contain bonuses and one time payments. We correct for this following Dustmann, Ludsteck, and Schönberg (2009).

Additionally, wages are top coded and the threshold differs across years. We impute the wages using the same main method as Card, Heining, and Kline (2013). We perform a series of 324 tobit imputations for age (21-30, 31-40, 41-50) times education (low, medium, high) times year (1975-2010) cells separately to allow for heteroskedasticity across groups and years. We therefore regress the observed, censored log wage on a constant, age, years of education, 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[7]. We use the predicted values $X'\beta$ from the tobit regressions together with the estimated standard deviation σ to impute the censored wages y^c as follows: $y^c = X'\beta + \sigma\Phi^{-1}[k + u(1-k)]$, where $u \sim U[0,1]$ and $k = \Phi[(c - X'\beta)/\sigma]$ and c is the censoring limit.

All of the analysis and imputation steps are weighted by the length of the spell which we use for the observation in one year as workers with longer spells will have higher yearly incomes than people with shorter spells.

3.2 QCS

The Qualification and Career Survey was conducted six times between 1979 and 2012. Participants were asked what tasks they perform on the job, e.g. "how often do you repair stuff?". We classify a task item to be either analytical, interactive, routine or manual. The mapping of task items into tasks can be found in appendix A.2. Within each wave, we assign each person a four dimensional task vector by averaging over the corresponding task items. Each element of the task vector is normed to lie in $[0,1]$. However, the four task measures do not necessarily sum up to one as we want to account for the fact that some occupations are more intense in

[7] 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.

all tasks than others. We append the six QCS waves and then average the task measures over professions.

In that respect we differ from Spitz-Oener (2006) as we do not consider the data to be well suited to derive time varying differences. We check our task measures on the occupation level by employing a very recent and unique dataset conducted by the BIBB as well (Task–Zusatzbefragung 2012)[8]. This survey collects information on the actual time which an employee spent with certain tasks and so very precise task measures can be derived. In 90% of the cases we can not reject equality between our computed measures employing the six waves and the measure derived from the Zusatzbefragung.

We construct the same occupation identifiers in both datasets and so combine them on the occupation level. We end up with a dataset with information on wage growth, occupational transitions, sociodemographics and task intensity data.

4 Stylized Facts

As already documented by other authors (Dustmann, Ludsteck, and Schönberg, 2009; Goos, Manning, and Salomons, 2009), employment in Germany, such as in most other developed countries, has polarized strongly starting in the mid 80's. In figure 2, we plot the change in employment shares over two time periods by skill percentiles. The skill of a worker is approximated by the mean years of education in 1975 within the occupation he works in. At the lower end of the skill distribution, mostly Service occupations are located. The middle consists of producing occupations contained in the professions Production/Operate and Craftsmen whereas high skill occupations can be found in the Sales/Office and Managers/Professionals/Technicians groups. We see that prior to 1985, there were employment gains at the top but no gains at the bottom of the skill distribution. We therefore call the period 1975–1984 the pre-polarization period. In contrast, the next 26 years are described by a dramatic polarization of the employment distribution. Both, low and high skill occupations reported dramatic employment gains whereas middling occupations lost employment.

[8]Unfortunately, the sample size is not high enough (N = 2272) to use this dataset alone.

Figure 2: Employment changes within occupational skill percentiles.

In figure 3, changes in employment shares relative to 1985 are shown. Consistent with figure 2, the professions found in the middle of the skill distribution lost employment while the remaining professions gained.

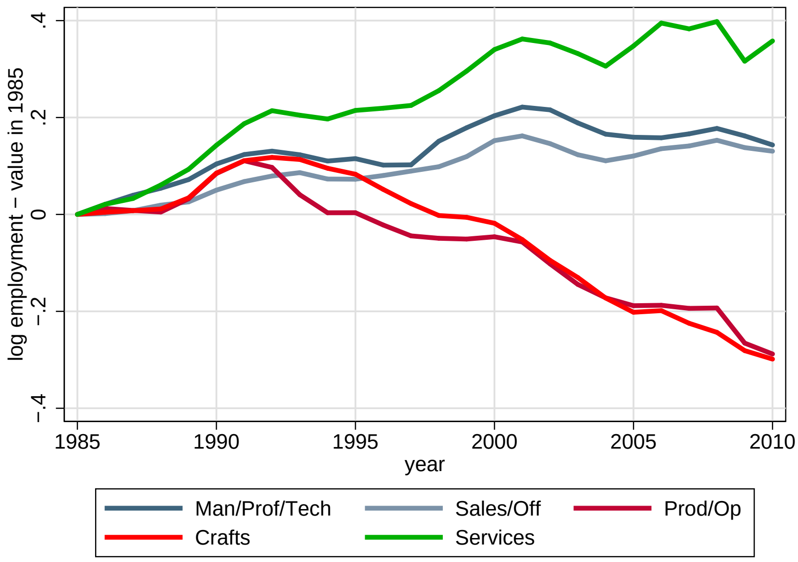


Figure 3: Employment in professions over time.

At the same, the wage distribution became much more dispersed as the upper percentiles gained relative to 1985 whereas the lower percentiles lost over time (see figure 4). As one may already suspect by the fact that the 10th percentile lost relative to 1985 and the greatest part of workers in Service occupations earns wages within this percentile, the wage distribution did not polarize.

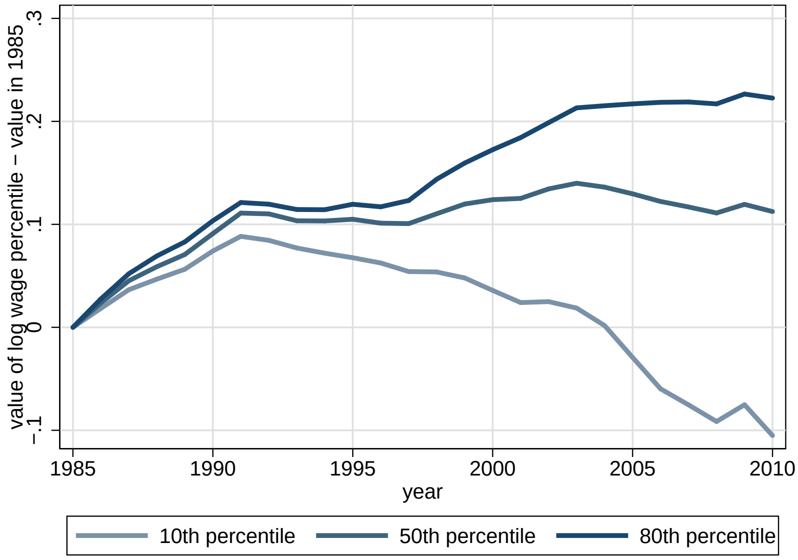
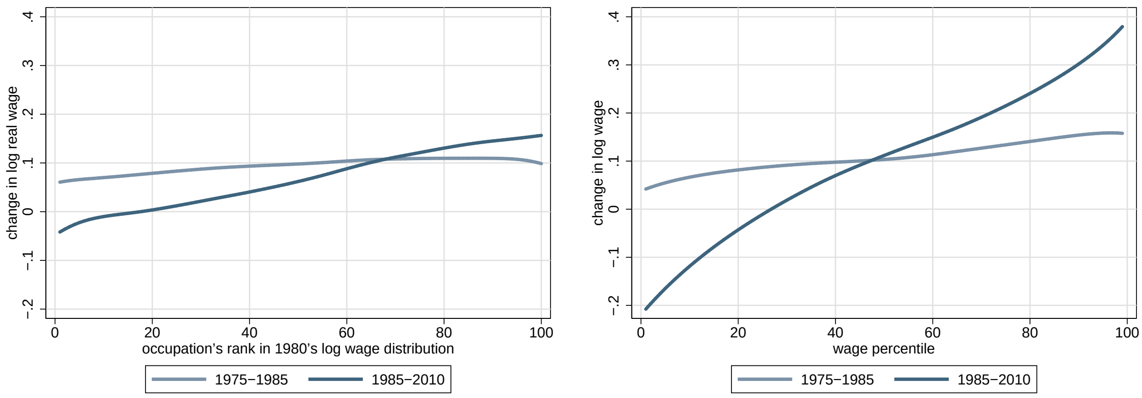


Figure 4: Wage percentiles over time.

As can be seen from figure 5, occupations from all parts of the skill distribution reported wage gains. However, those were largest for the high skill occupations. The pre-polarization era was characterized by equal gains across the skill distribution.



(a) Wage changes within occupational skill percentiles.

(b) Wage changes by wage percentiles.

Figure 5: Wage polarization.

Figure 6 shows that the polarization did not occur because mean Service wages did not rise relative to middling occupations but even lost.

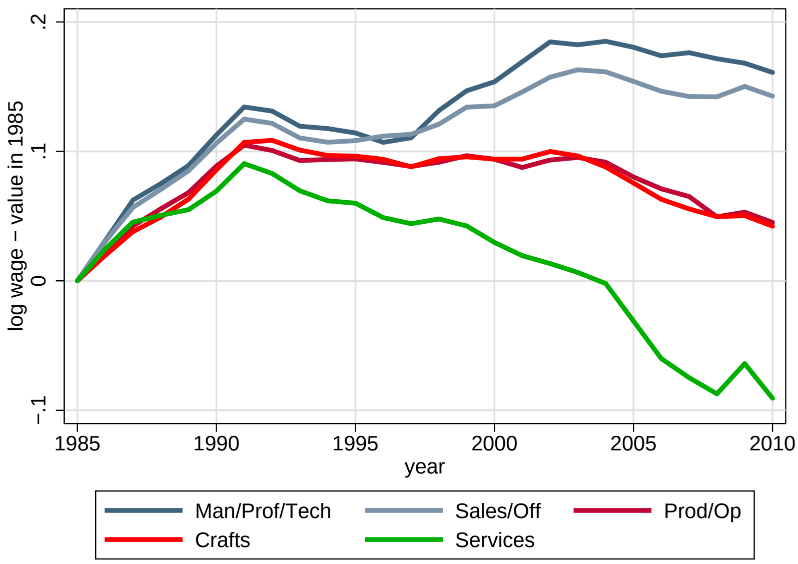


Figure 6: Wages in professions over time.

As already discussed in section 1, routine-biased technological change does not necessarily imply wage polarization as wage changes are a mixture of price and composition effects (Autor, Katz, and Kearney, 2006). However, skill prices should polarize over time when one accounts for the self selection and thereby accounts for composition effects. The value for skills necessary for occupations intense in routine tasks should decrease over time relative to skills necessary for occupations who are less vulnerable to automation and offshoring.

5 Estimation Results

In this section, we present the estimation results for the price changes as given by equation 13. Figure 7 shows the estimated yearly task price changes. Skills are modeled to be acquired on the job by performing tasks and the speed of the accumulation depends on age.

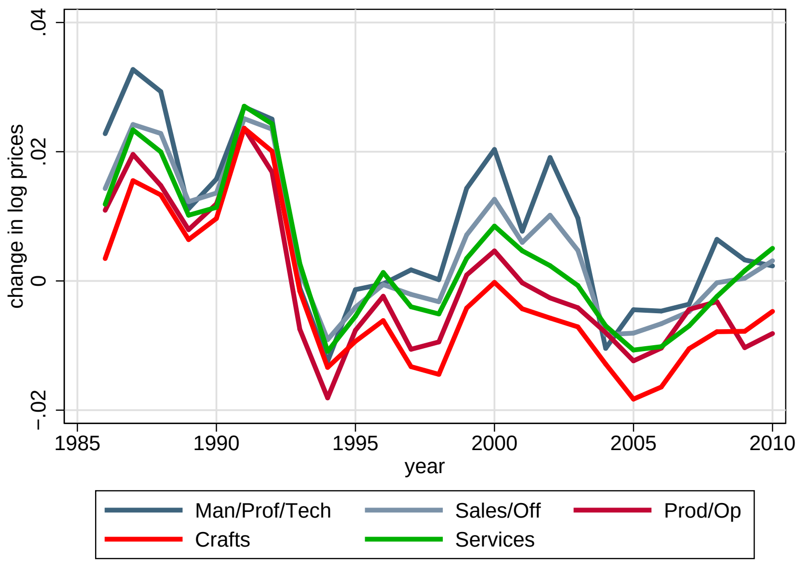


Figure 7: Estimated yearly task price changes $\Delta\pi_{k,t}$.

If we sum the yearly price changes up, we receive absolute prices relative to the prices in the pre-polarization era as the identification of the skill accumulation equation relied on the fact that prices evolved at the same speed in the pre-polarization era as described by 12. The results are shown in figure 8.

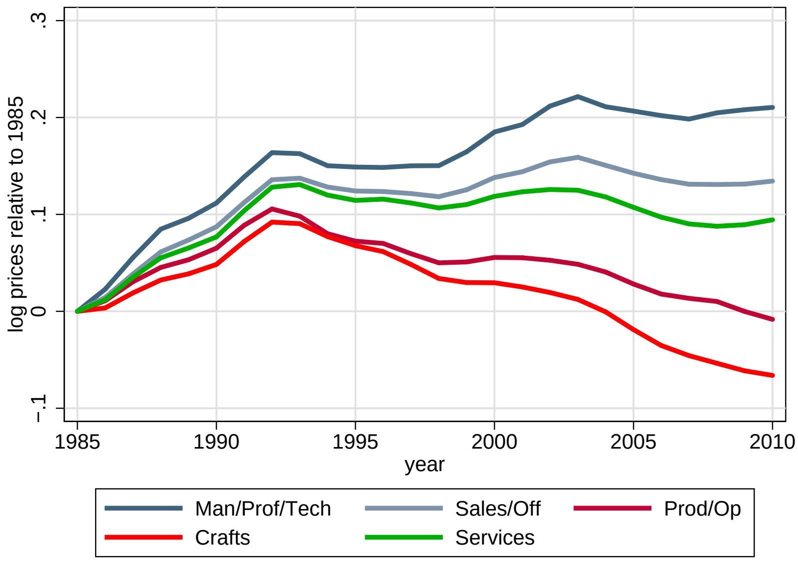


Figure 8: Absolute yearly task prices relative to the prices in 1985, $\sum_{t=1985}^{2010} \Delta\pi_{k,t}$.

To get rid of the trend $\bar{\pi}$ which is common to all of the estimated prices above, we can subtract the estimated price of a baseline group from all other prices as the additive trend is the assumed to be the same for the prices of all professions. We use the middling profession Production/Operate as the baseline group so that we can easily identify whether prices polarized or note. The resulting estimates are shown in figure 9.

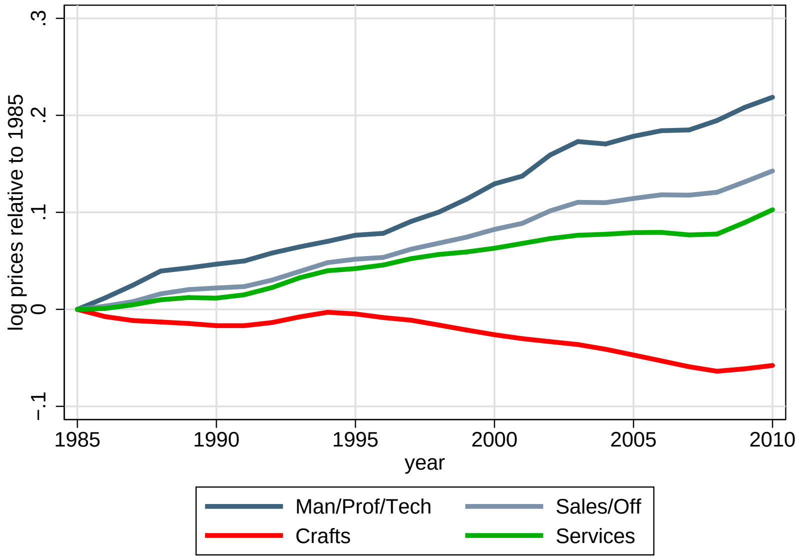


Figure 9: Absolute yearly task prices relative to the prices in 1985 and relative to the prices of the baseline group Production/Operate, $\sum_{t=1985}^{2010} \Delta\pi_{k,t} - \Delta\pi_{\text{Prod/Op},t}$.

Prices paid for skills in professions intense in analytical, interactive and manual tasks rose. Whereas, the prices for middling professions stagnated or even fell. This finding is what we call skill price polarization. As Goldschmidt and Schmieder (2015) point out, Service jobs have been increasingly outsourced into distinct firms in Germany within the last two decades. Hence, in total, we may even underestimate the price increase for Service jobs as firms who employ the outsourced workers pay less on average than their former firms.

The change in employment is consistent with the change in prices. Employment in the margin professions rose as did their prices, employment in middling professions as well as the prices paid for skills in those. However, wages did not behave like prices as Service wages did not rise. The implication from our model is that mean skills within Services most have offset a potential rise in wages. The next section explores this in greater detail.

6 Reconciling the Facts

6.1 Elasticities

The easiest thing to do is to calculate cross price elasticities of employment for each profession k with respect to a baseline profession j. We calculate those as follows:

$$\varepsilon_{k/j,t} = \frac{\Delta\%(\text{employment}_{k,t})}{\Delta\pi_{j,t}} \tag{15}$$

Those elasticities answer the question, how employment in k reacts to a one percentage point change in the price of j between t and $t-1$.

The results can be found in table 1.

empl. in k / price for j	Man/Prof/Tech	Sales/Off	Prod/Op	Crafts	Services
Man/Prof/Tech	0.41	0.85	-3.15	-3.23	2.43
Sales/Off	0.85	1.77	-6.59	-6.75	5.09
Prod/Op	-0.55	-1.14	4.23	4.34	-3.27
Crafts	-0.35	-0.73	2.72	2.79	-2.10
Services	2.27	4.75	-17.62	-18.07	13.61

Table 1: Cross price elasticities between 1990 and 2010.

As you can see, the magnitude of the results is largest for the relation between middling professions and Services. If the price for Service skills rises one percentage point faster than in the pre-polarization period, employment in middling professions declines by roughly 17 percentage points. The same is true for the other two professions at the fringes. Hence, a price increase for professions on the margins seems to absorb workers from middling professions. If prices for the middling professions rise, then this effect also appears, i.e. workers from the fringes are absorbed into the middle, but the effect is much smaller in magnitude.

6.2 Decompositions

If low skilled workers from middling professions moved to Services, then wage polarization would not necessarily occur although the price paid for Service skills rose. The new mean Service worker could then have lower skills because of a negative selection out of Production/Operate and into Services. In addition, Service workers could have lower life cycle skill accumulation on average if there is much turnover, i.e. if Service workers' often switch into unemployment, other professions or out of the labor force. Our estimates allow us to disentangle those channels. We do so by proceeding as follows:

1. We first plot the implied skill changes within professions over time. We make use of the identity defined in 1, i.e. $w_{i,t} = w_{k,i,t} = \pi_{k,t} + s_{k,i,t}$ if $I_{k,i,t} = 1$. If we take expectations conditional on all workers being in k on both sides, we end up with:

$$\mathrm{E}[w_{i,t}|I_{k,i,t} = 1] = \pi_{k,t} + \mathrm{E}[s_{k,i,t}|I_{k,i,t} = 1] \tag{16}$$

Taking first differences of this equation yields:

$$\mathrm{E}[w_{i,t}|I_{k,i,t} = 1] - \mathrm{E}[w_{i,t-1}|I_{k,i,t-1} = 1] - \Delta\pi_{k,t} = \mathrm{E}[s_{k,i,t}|I_{k,i,t} = 1] - \mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1} = 1] \tag{17}$$

The resulting skill change estimates contain the change in mean skills within profession k from one period to the next. We receive them as a residual from mean wage changes and price changes. In figure 10, we accumulate the year to year change in mean skills, prices and wages of the sample analogues of $\mathrm{E}(\cdot)$ for all of the professions[9].

[9] In the following figures, we rely on the assumption that prices did not change at all in the pre-polarization period, i.e. $\Delta\pi_{k,t} = \bar{\pi} = 0, t \leq 1984$. If we stay with the less restrictive assumption that prices did not change relative to each other, i.e. $\Delta\pi_{k,t} = \bar{\pi}, t \leq 1984$, we are only able to estimate relative price changes. Hence, we would need to subtract skills from a baseline group somehow. For the first exercise, this is not a problem. However, for the more detailed decompositions in the next steps, it gets complicated as entrant and exit probabilities are not equal across professions ($h^e_{k,t} \neq h^e_{j,t}, j \neq k$ and $h^o_{k,t-1} \neq h^o_{j,t-1}, j \neq k$)).

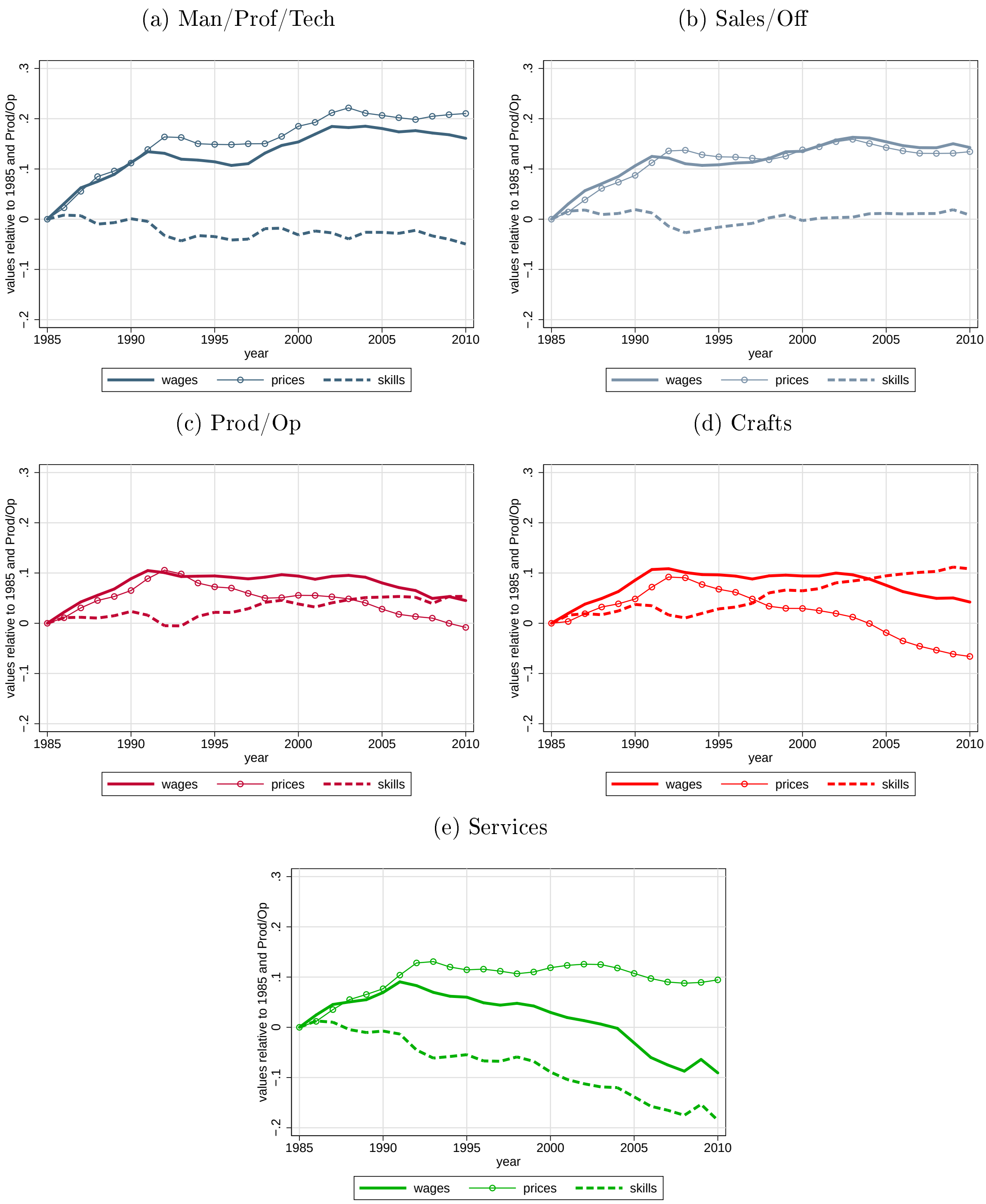


Figure 10: Decomposition of mean wages into prices and skills relative to Prod/Op and 1985.

You see that skills within Services decrease very fast, whereas the other stay constant or increase. However, the fact that prices increase suggests that there is either a negative selection of workers from different professions, unemployment or out of the labor force into Services taking place, or Service workers accumulate skills more slowly.

2. To disentangle those channels, we further decompose the mean skill changes within professions. Therefore, denote with $h^e_{k,t} = P(I_{k,i,t-1} = 0|I_{k,i,t} = 1)$ the fraction of workers who work in profession k at time t but did not so at $t-1$, i.e. the share of entrants. Further, let $h^o_{k,t-1} = P(I_{k,i,t} = 0|I_{k,i,t-1} = 1)$ bet the fraction of workers who worked in k at $t-1$ but did not do so anymore at t, i.e. the fraction of leavers.

By the law of total expectations, we can split up the terms defined in 17 as follows:

(18)

$$\begin{aligned} &\mathrm{E}[s_{k,i,t}|I_{k,i,t} = 1] - \mathrm{E}[s_{k,i,t-1}|I_{k,i,t-1} = 1] \\ &= (1 - h^e_{k,t})\mathrm{E}[s_{k,i,t}|I_{k,i,t} = I_{k,i,t-1} = 1] + h^e_{k,t}\mathrm{E}[s_{k,i,t}|I_{k,i,t} = 1, I_{k,i,t-1} = 0] \\ &- (1 - h^o_{k,t-1})\mathrm{E}[s_{k,i,t-1}|I_{k,i,t} = I_{k,i,t-1} = 1] - h^o_{k,t-1}\mathrm{E}[s_{k,i,t-1}|I_{k,i,t} = 0, I_{k,i,t-1} = 1] \end{aligned}$$

(19)

$$= \underbrace{(1 - h^e_{k,t})\mathrm{E}[\Delta s^s_{k,i,t}]}_{\text{accumulation}} + \underbrace{h^e_{k,t}[\mathrm{E}[s^e_{k,i,t}] - \mathrm{E}[s^o_{k,i,t-1}]] + (h^o_{k,t-1} - h^e_{k,t})[\mathrm{E}[s^s_{k,i,t-1}] - \mathrm{E}[s^o_{k,i,t-1}]]}_{\text{selection}}$$

In this notation, s (stayer) describes the conditioning set given by $\{I_{k,i,t} = I_{k,i,t-1} = 1\}$, e (entrant) describes $\{I_{k,i,t} = 1, I_{k,i,t-1} = 0\}$ and o (leaver) describes $\{I_{k,i,t} = 0, I_{k,i,t-1} = 1\}$.

As the prices are the same for all of the groups of stayers, entrants and leavers, we are able to compute the empirical analogue for the accumulation and selection parts in equation 19 as:

$$\mathrm{E}[\Delta s^s_{k,i,t}] = \mathrm{E}[\Delta w^s_{k,i,t}] - \Delta\pi_{k,t} \tag{20}$$

$$\mathrm{E}[s^e_{k,i,t}] - \mathrm{E}[s^o_{k,i,t-1}] = \mathrm{E}[\Delta w^e_{k,i,t}] - \mathrm{E}[\Delta w^o_{k,i,t-1}] - \Delta\pi_{k,t} \tag{21}$$

$$\mathrm{E}[s^s_{k,i,t-1}] - \mathrm{E}[s^o_{k,i,t-1}] = \mathrm{E}[w^s_{k,i,t-1}] - \mathrm{E}[w^o_{k,i,t-1}] \tag{22}$$

The interpretation of the parts in 19 is as follows:

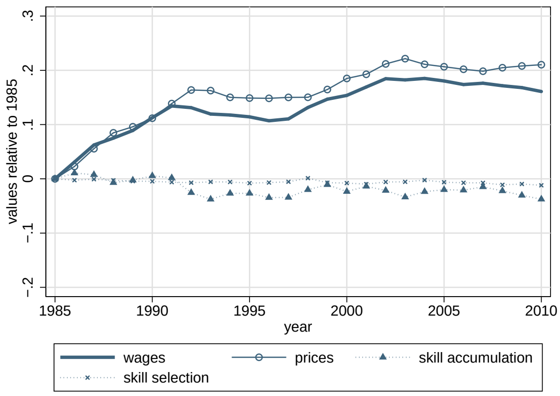
On the one hand, skills could fall relative to the baseline group as the skill accumulation could get worse. This might happen because workers transition in and out of, say, Services (much turnover) and so have career breaks which are penalized through a lower skill accumulation.

On the other hand, skills could fall because of negative selection effects. The first part of the selection term describes a possible negative influence of entrants if $\mathrm{E}[s^e_{k,i,t}] < \mathrm{E}[s^o_{k,i,t-1}]$, i.e. if entrants into Services are much worse than the workers who leave Services.

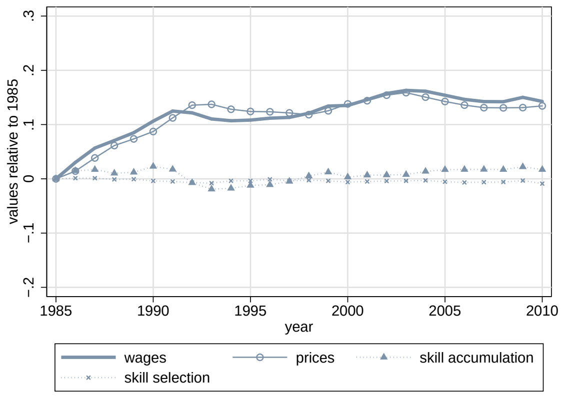
The second part of the selection term is an adjustment factor and is more subtle (and what now comes is not fully right). If a profession k is shrinking over time, then $h^o_{k,t-1} > h^e_{k,t}$ which is the case for the middling professions but reversed for the professions on the margins. In addition, if $\mathrm{E}[s^s_{k,i,t-1}] > \mathrm{E}[s^o_{k,i,t}]$, then low skilled people leave k and so selection is less worse for the declining profession.

The incremental results can be seen in appendix figure 17. The accumulated results of this exercise together with wages and prices in figure 11.

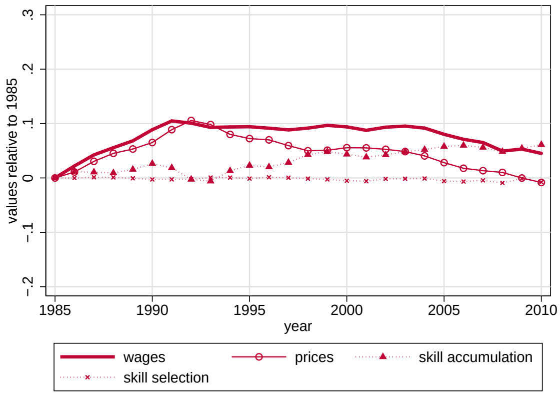
(a) Man/Prof/Tech



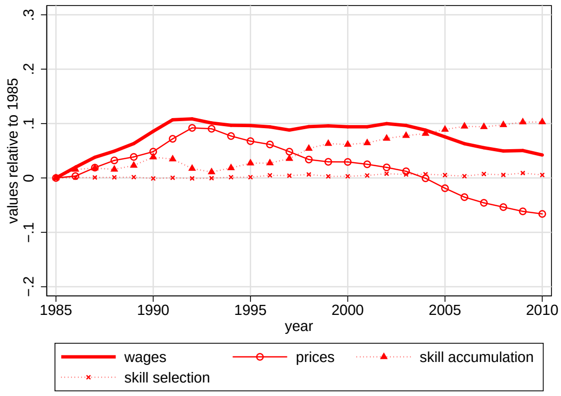
(b) Sales/Off



(c) Prod/Op



(d) Crafts



(e) Services

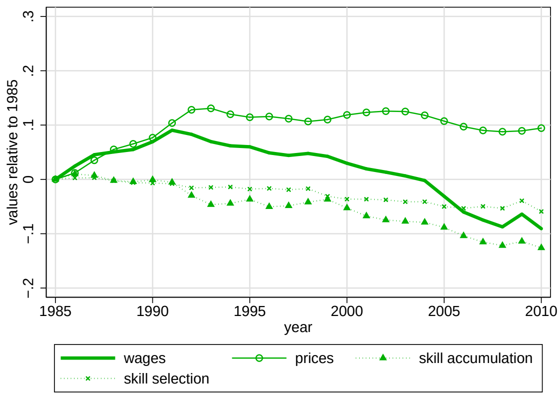


Figure 11: Decomposition of mean wages into prices and skills relative to 1985.

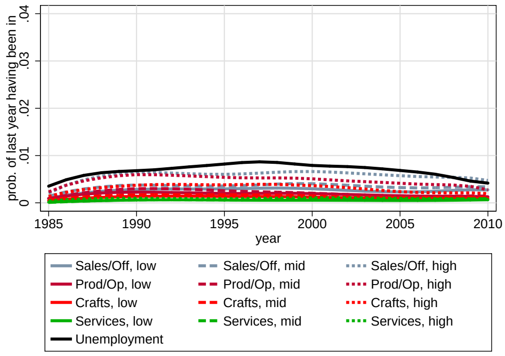
You see that the greatest part of the changes in skills are explained by changes in the accumulation process except for Services where the influence of selection on the deterioration of mean skills is also quite substantial. This finding could be explained by the possibility that high skill workers in middling professions stay within their profession for longer time and so accumulate more skills whereas there is more turnover in Services as well as negative drain of low skilled middling workers into this profession. Because of more turnover the accumulation suffers as people in Services may have disproportionately more career breaks which worsens their accumulation of skills. In addition, the increasing price for Service skills may attract low skilled workers from middling professions where the price does not increase.

6.3 Plausibility checks

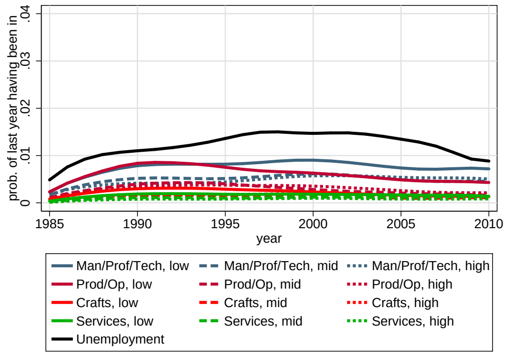
6.3.1 Selection

To check for plausibility of our estimates, we compute yearly transition probabilities into Services from profession–wage–percentile bins and from unemployment. Figure 12 shows the results.

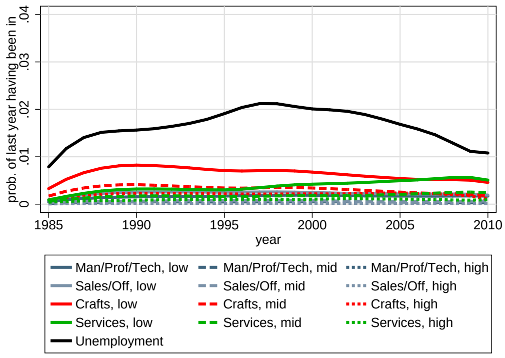
(a) Man/Prof/Tech



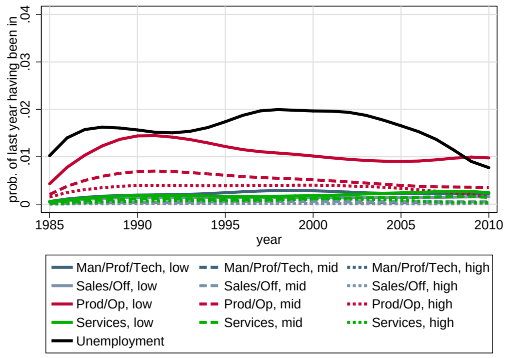
(b) Sales/Off



(c) Prod/Op



(d) Crafts



(e) Services

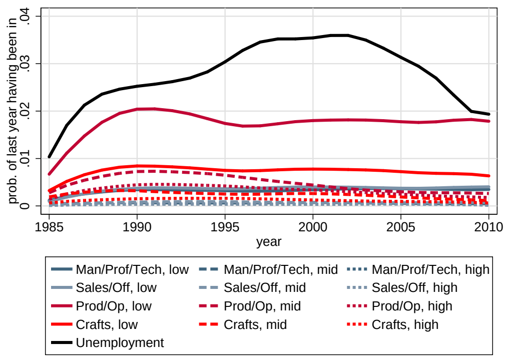
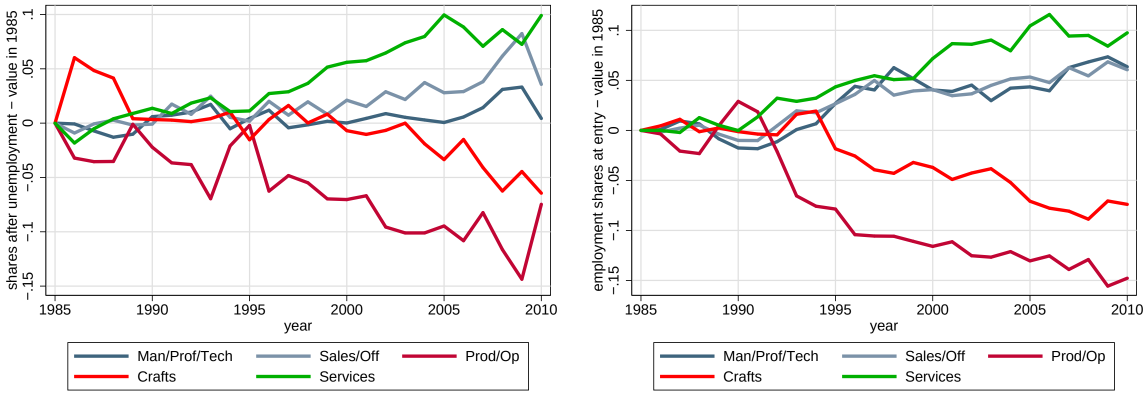


Figure 12: Yearly transition probabilities from all other professions and unemployment at time $t-1$ into Services at time t. Low represents workers in the lower third wage percentile within a profession (the low skilled workers). Mid stands for workers in the 34-66th wage percentile, whereas high represents workers in the upper third. Switches and stayers within Services are not plotted in this graph but are in the calculations.

You see that the probability to move into Services is highest for workers from middling professions and unemployment. And, in addition, it is especially high for workers with a low wage in the middling professions. If we assume that those workers are the lowest skilled workers within their former professions, then this finding is consistent with our hypothesis that wage polarization did not occur because of a negative skill selection out of the middle and into the bottom.



(a) Unemployment

(b) Labor market entry.

Figure 13: Selection from unemployment and at entry.

In addition, figure 13 shows into which professions workers transition after unemployment and at labor market entry. You see that middling occupations are less likely in 2010 to be entered than 1985 and Services became more likely. This suggests that less able workers move into Services today and thereby worsen the skill structure.

6.3.2 Accumulation

Workers in middling professions were 2.5 years older in 2010 than in 1985 whereas workers in professions at the fringes were only 1.3 years older. Consistently with the work of Autor and Dorn (2009), the workforce in middling professions is getting old. This may happen as retiring workers are not replaced anymore or young workers' jobs are destroyed more often within recessions than those of older workers (Jaimovich and Siu, 2014). Although, the pace at which young workers acquire skills is higher for young than for old workers (see figure 14), experienced workers have higher mean skills than the young. Therefore, the accumulation channel may be slightly positive for middling professions. In addition, jobs at the fringes have higher degress of mobility as workers transition in and out over time and so workers within those professions have interruptions in their labor market histories more often leading to less skill accumulation.

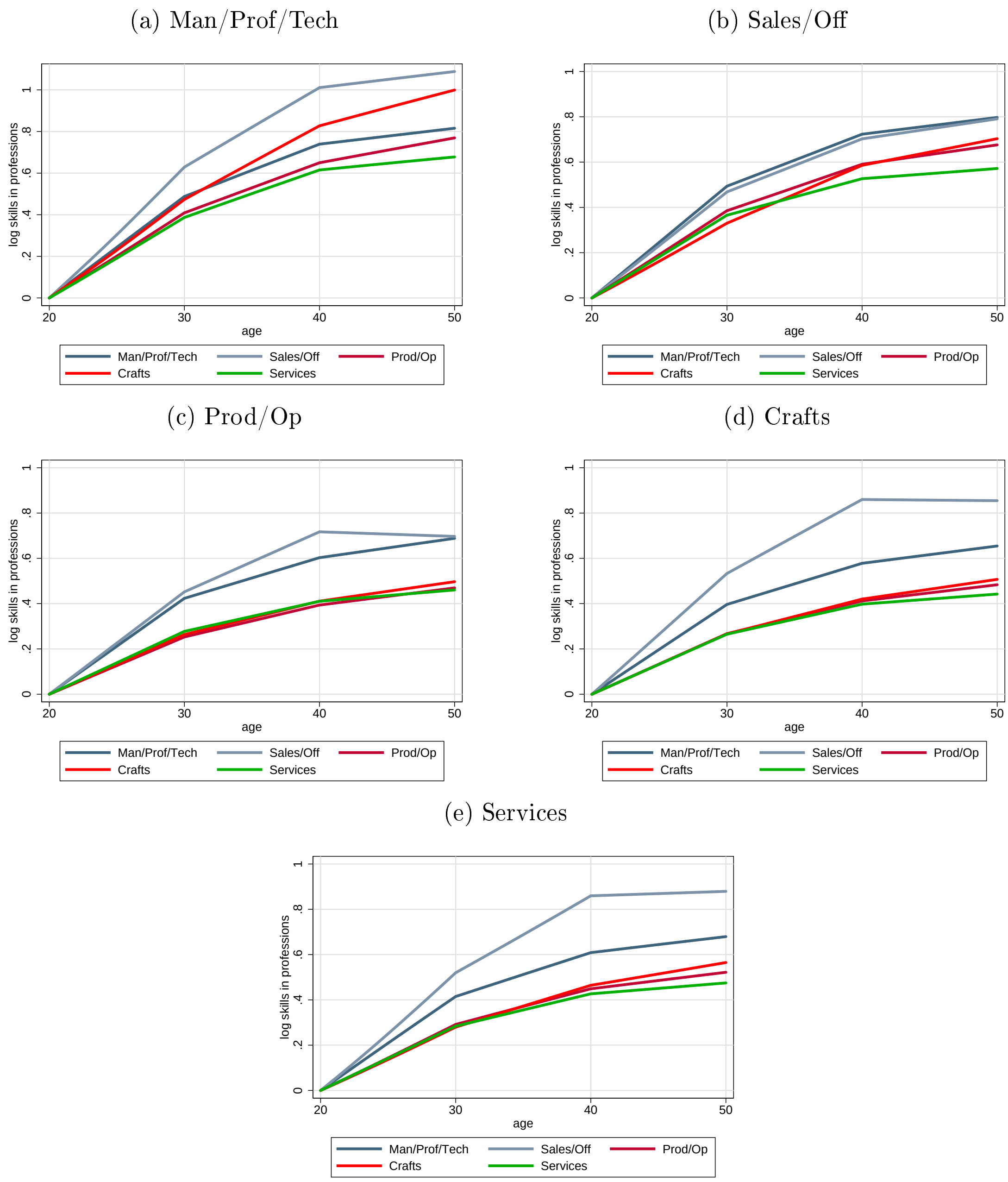


Figure 14: Skill accumulation over age. We present the parameter estimates and therefore the skill accumulation estimates for a hypothetical worker who stayed within one profession over his whole working period, i.e. between ages 21 and 50. As suspected, the acquisition is concave over the life cycle for all professions and highest for high skill occupations.

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A Appendix

A.1 Mapping of Occupations into Professions

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

Continued on next page

	Butchers until fish processing operatives
	Carpenters
	Carpenters until scaffolders
	Cutters until textile finishers
	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.

Continued on next page

	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
	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)

Continued on next page

	Cashiers
	Cooks until ready-to-serve meals, fruit, vegetable preservers, preparers
	Dental technicians until doll makers, model makers, taxidermists
	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

A.2 Generation of Task Variables

		1979	1986	1992	1999	2006	2012
analytical	tsk_analyze						
	tsk_draw		Künstlerisch gestalten, zeichnen	Künstlerisch gestalten, zeichnen			
	tsk_fraction_calculus						
	tsk_higher_calculus						
	tsk_information_search				Wie häufig kommt Informationen sammeln / Recherchieren / Dokumentieren bei Ihrer Arbeit vor?	Wie häufig kommt Informationen sammeln / Recherchieren / Dokumentieren bei Ihrer Arbeit vor?	Wie häufig kommt Informationen sammeln / Recherchieren / Dokumentieren bei Ihrer Arbeit vor?
	tsk_law	Gesetze anwenden, Personen in Rechtsfragen beraten	Gesetze auslegen, Vorschriften anwenden	Gesetze auslegen, Vorschriften anwenden	Gesetze auslegen, Vorschriften anwenden		
	tsk_plan_develop	Projektieren, planen, Konstruieren, entwerfen, skizzieren					
	tsk_read_25_pages						
	tsk_read_five_pages						
	tsk_read_one_page						

Continued on next page

		1979	1986	1992	1999	2006	2012
	tsk_research_construct	Forschen, erkunden	Entwicklen, forschen, Konstruieren	Entwicklen, forschen, Konstruieren	Wie häufig kommt Entwickeln / Forschen / Konstruieren bei Ihrer Arbeit vor?	Wie häufig kommt Entwickeln / Forschen / Konstruieren bei Ihrer Arbeit vor?	Wie häufig kommt Entwickeln / Forschen / Konstruieren bei Ihrer Arbeit vor?
	tsk_simple_calculus						
	tsk_solve_problems						
	tsk_surface_calculus						
	tsk_write_25_pages						
	tsk_write_five_pages						
	tsk_write_one_page						
interactive	tsk_applicant						
	tsk_apprentice_training		Ausbildung von Lehrlingen				
	tsk_buy_sell		Einkaufen, Beschaffen, Verkaufen	Einkaufen, Beschaffen, Verkaufen	Wie häufig kommt Einkaufen / Beschaffen / Verkaufen bei Ihrer Arbeit vor?	Wie häufig kommt Einkaufen / Beschaffen / Verkaufen bei Ihrer Arbeit vor?	Wie häufig kommt Einkaufen / Beschaffen / Verkaufen bei Ihrer Arbeit vor?
	tsk_consult				Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?	Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?	Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?

Continued on next page

	1979	1986	1992	1999	2006	2012
				Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?	Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?	Wie häufig kommt Beraten / Informieren bei Ihrer Arbeit vor?
tsk_disclosure						
tsk_interact_people						
tsk_marketing_pr				Werben, Marketing oeffentlichkeitsarbeit, PR	Wie häufig kommt Werben / Marketing / Öffentlichkeitsarbeit / PR bei Ihrer Arbeit vor?	Wie häufig kommt Werben / Marketing / Öffentlichkeitsarbeit / PR bei Ihrer Arbeit vor?
tsk_negotiate	Verhandeln, Interessen vertreten					
tsk_organise	Koordinieren, organisieren	Organisieren, Planen	Organisieren, Planen	Wie häufig kommt Organisieren / Planen und Vorbereiten von Arbeitsprozessen bei Ihrer Arbeit vor?	Wie häufig kommt Organisieren / Planen und Vorbereiten von Arbeitsprozessen bei Ihrer Arbeit vor?	Wie häufig kommt Organisieren / Planen und Vorbereiten von Arbeitsprozessen bei Ihrer Arbeit vor?

Continued on next page

	1979	1986	1992	1999	2006	2012
tsk_personnel_supervision			Vorgesetzter sein, Personal einstellen, Mitarbeiter anleiten			
tsk_persuade				Wie häufig müssen Sie andere überzeugen und Kompromisse aushandeln?		
tsk_publish	Publizieren, Journalistisch arbeiten	Publizieren, unterhalten, Vortragen	Publizieren, unterhalten, Vortragen			
tsk_standby						
tsk_supervision				Haben Sie Mitarbeiter und Mitarbeiterinnen, für die Sie direkte Vorgesetzte sind?	Haben Sie Mitarbeiter und Mitarbeiterinnen, für die Sie direkte Vorgesetzte sind?	Haben Sie Mitarbeiter und Mitarbeiterinnen, für die Sie direkte Vorgesetzte sind?

Continued on next page

		1979	1986	1992	1999	2006	2012
	tsk_teach	Erziehen, ausbilden	Erziehen, Lehren	Erziehen, Lehren	Wie häufig kommt Ausbilden / Lehren / Unterrichten / Erziehen bei Ihrer Arbeit vor?	Wie häufig kommt Ausbilden / Lehren / Unterrichten / Erziehen bei Ihrer Arbeit vor?	Wie häufig kommt Ausbilden / Lehren / Unterrichten / Erziehen bei Ihrer Arbeit vor?
routine	tsk_cash						
	tsk_machine	Maschinen/Technische Anlagen fahren, bedienen, einrichten, warten	Maschinen Steuern, Machischnen einrichten	Maschinen Steuern, Machischnen einrichten			

Continued on next page

	1979	1986	1992	1999	2006	2012
tsk_manufacture	Schädlinge bekämpfen, düngen, Rohstoffe gewinnen, Rohstoffe aufbereiten, Zentrifugieren, Schmelzen, Gießen, Chemische Produkte erzeugen, Mahlen, pressen, Brauen, Brennen, Weben, spinnen, Gerben, konservieren, Walzen, ausformen, Materialoberflächen behandeln, Veredeln, anreichern, Waren auszeichnen, Maschinenschreiben					

Continued on next page

		1979	1986	1992	1999	2006	2012
	tsk_measure	Vermessen					
	tsk_operate				Wie häufig kommt Überwachen / Steuern von Maschinen / Anlagen / techn. Prozessen bei Ihrer Arbeit vor?	Wie häufig kommt Überwachen / Steuern von Maschinen / Anlagen / techn. Prozessen bei Ihrer Arbeit vor?	Wie häufig kommt Überwachen / Steuern von Maschinen / Anlagen / techn. Prozessen bei Ihrer Arbeit vor?
	tsk_plant_substance		Pflanzen anbauen, um Tiere kümmern, Stoffe bearbeiten, Speisen bereiten	Pflanzen anbauen, um Tiere kümmern, Stoffe bearbeiten, Speisen bereiten, Rohstoffe gewinnen			
	tsk_produce				Wie häufig kommt Herstellen / Produzieren von Waren und Gütern bei Ihrer Arbeit vor?	Wie häufig kommt Herstellen / Produzieren von Waren und Gütern bei Ihrer Arbeit vor?	Wie häufig kommt Herstellen / Produzieren von Waren und Gütern bei Ihrer Arbeit vor?

Continued on next page

		1979	1986	1992	1999	2006	2012
	tsk_quality_check				Wie häufig kommt Messen / Prüfen / Qualitätskontrolle bei Ihrer Arbeit vor?	Wie häufig kommt Messen / Prüfen / Qualitätskontrolle bei Ihrer Arbeit vor?	Wie häufig kommt Messen / Prüfen / Qualitätskontrolle bei Ihrer Arbeit vor?
	tsk_transport		Packen, versenden, transportieren			Wie häufig kommt Transportieren / Lagern / Versenden bei Ihrer Arbeit vor?	Wie häufig kommt Transportieren / Lagern / Versenden bei Ihrer Arbeit vor?
	tsk_transport_sort			Packen, versenden, transportieren, Sortieren, archivieren			
manual	tsk_care						
	tsk_clean		Putzen, bügeln, reinigen			Wie häufig kommt Reinigen, Abfall beseitigen, Recyclen bei Ihrer Arbeit vor	Wie häufig kommt Reinigen, Abfall beseitigen, Recyclen bei Ihrer Arbeit vor

Continued on next page

	1979	1986	1992	1999	2006	2012
tsk_clean_host_care			Putzen, bügeln, reinigen, Abfall beseitigen, Pflegen, versorgen, Bewirten, Beherbergen, Speisen bereiten			
tsk_conduct			Fahrzeuge steuern			
tsk_dexterity						
tsk_hospitality				Wie häufig kommt Bewirten / Beherbergen / Speisenbereiten bei Ihrer Arbeit vor?		
tsk_host_care		Pflegen, versorgen, Bewirten, Beherbergen, Speisen bereiten			Pflegen, versorgen, Bewirten, Beherbergen, Speisen bereiten	Pflegen, versorgen, Bewirten, Beherbergen, Speisen bereiten

Continued on next page

	1979	1986	1992	1999	2006	2012
tsk_household_host_care	Haushalt führen, Bewirten, beherbergen, Betreuen, pflegen					
tsk_means_of_transportation				Arbeit mit Transportmitteln		
tsk_physical_strength						
tsk_reaction						
tsk_repair				Wie häufig kommt Reparieren / Instandsetzen bei Ihrer Arbeit vor?	Wie häufig kommt Reparieren / Instandsetzen bei Ihrer Arbeit vor?	Wie häufig kommt Reparieren / Instandsetzen bei Ihrer Arbeit vor?
tsk_repair_construct		Ausbessern, Instandsetzen, Restaurieren, ausbessern, Gebäude und Anlagen bauen, installieren	Ausbessern, Instandsetzen, Restaurieren, ausbessern, Gebäude und Anlagen bauen, installieren			
tsk_restore	Restaurieren					

Continued on next page

		1979	1986	1992	1999	2006	2012
	tsk_secure	Sichern, bewachen	Sichern, bewachen	Sichern, bewachen		Wie häufig kommt Sichern / Schützen / Bewachen/Überwachen / Verkehr regeln bei Ihrer Arbeit vor?	Wie häufig kommt Sichern / Schützen / Bewachen/Überwachen / Verkehr regeln bei Ihrer Arbeit vor?
	tsk_waste_clean	Reinigen, Müll beseitigen					

	analytical	interactive	routine	manual
Man/Prof/Tech	0.34	0.39	0.18	0.14
Sales/Off	0.15	0.30	0.15	0.09
Prod/Op	0.09	0.15	0.33	0.23
Crafts	0.10	0.19	0.30	0.28
Services	0.17	0.27	0.20	0.26

Table 4: Mean task measures by profession.

A.3 Derivation of Equation 9

Plug in the approximation from 8 into 7, to get:

$$
\begin{aligned}
\Delta w_{i,t} &= \Delta w_{j,i,t} + \sum_{k=1,k\neq j}^{K} \int_{\tilde{w}_{k,i,t-1}}^{\tilde{w}_{k,i,t}} I_{k,i,t-1} + \frac{I_{k,i,t} - I_{k,i,t-1}}{\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}} (\tilde{w}_{k,i,\tau} - \tilde{w}_{k,i,t-1}) d\tilde{w}_{k,i,\tau} \\
&= \Delta w_{j,i,t} + \sum_{k=1,k\neq j}^{K} I_{k,i,t-1}(\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}) + \frac{1}{2}\frac{I_{k,i,t} - I_{k,i,t-1}}{\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}}(\tilde{w}_{k,i,t}^2 - \tilde{w}_{k,i,t-1}^2) \\
&- \frac{I_{k,i,t} - I_{k,i,t-1}}{\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}} \tilde{w}_{k,i,t-1}(\tilde{w}_{k,i,t} - \tilde{w}_{k,i,t-1}) \\
&= \Delta w_{j,i,t} + \sum_{k=1,k\neq j}^{K} I_{k,i,t-1}\tilde{w}_{k,i,t} - I_{k,i,t}\tilde{w}_{k,i,t-1} + \frac{1}{2} I_{k,i,t}\tilde{w}_{k,i,t} + \frac{1}{2} I_{k,i,t}\tilde{w}_{k,i,t-1} \\
&- \frac{1}{2} I_{k,i,t-1}\tilde{w}_{k,i,t} - \frac{1}{2} I_{k,i,t-1}\tilde{w}_{k,i,t-1} \\
&= \Delta\pi_{j,t} + \Delta s_{j,i,t} + \sum_{k=1,k\neq j}^{K} \frac{1}{2} I_{k,i,t-1}(\pi_{k,t} - \pi_{j,t} + s_{k,i,t} - s_{j,i,t}) - \\
&\frac{1}{2} I_{k,i,t}(\pi_{k,i,t-1} - \pi_{j,i,t-1} + s_{k,i,t-1} - s_{j,i,t-1}) \\
&+ \frac{1}{2} I_{k,i,t}(\pi_{k,t} - \pi_{j,t} + s_{k,i,t} - s_{j,i,t}) - \frac{1}{2} I_{k,i,t-1}(\pi_{k,i,t-1} - \pi_{j,i,t-1} + s_{k,i,t-1} - s_{j,i,t-1}) \\
&= \Delta\pi_{j,t} + \Delta s_{j,i,t} + \sum_{k=1,k\neq j}^{K} \frac{1}{2} I_{k,i,t-1}(\Delta\pi_{k,t} - \Delta\pi_{j,t} + \Delta s_{k,i,t} - \Delta s_{j,i,t}) \\
&+ \frac{1}{2} I_{k,i,t}(\Delta\pi_{k,t} - \Delta\pi_{j,t} + \Delta s_{k,i,t} - \Delta s_{j,i,t}) \\
&= \Delta\pi_{j,t} + \Delta s_{j,i,t} + \sum_{k=1,k\neq j}^{K} \frac{I_{k,i,t} + I_{k,i,t-1}}{2}(\Delta\pi_{k,t} - \Delta\pi_{j,t} + \Delta s_{k,i,t} - \Delta s_{j,i,t}) \\
&= \Delta\pi_{j,t} + \Delta s_{j,i,t} + \sum_{k=1,k\neq j}^{K} \bar{I}_{k,i,t}(\Delta\pi_{k,t} - \Delta\pi_{j,t}) + \bar{I}_{k,i,t}(\Delta s_{k,i,t} - \Delta s_{j,i,t})
\end{aligned}
$$

A.4 Additional Figures

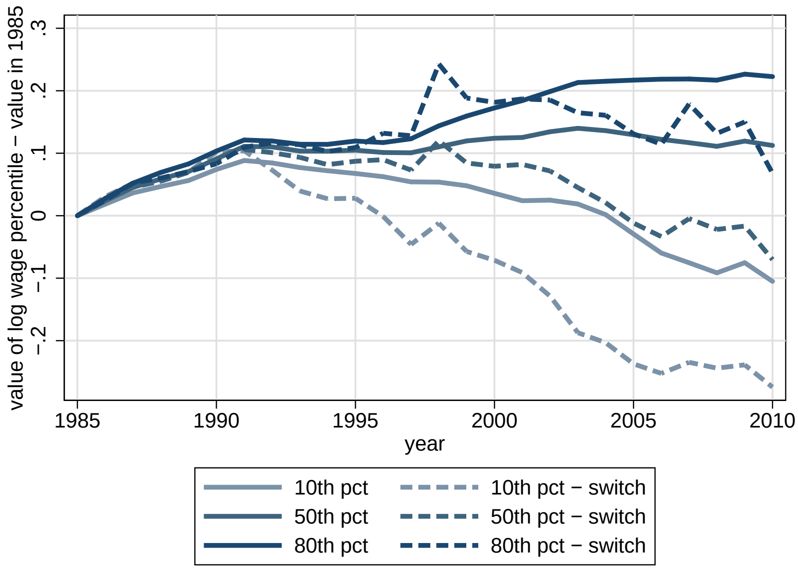
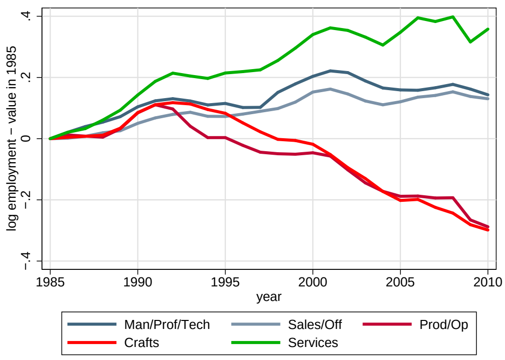
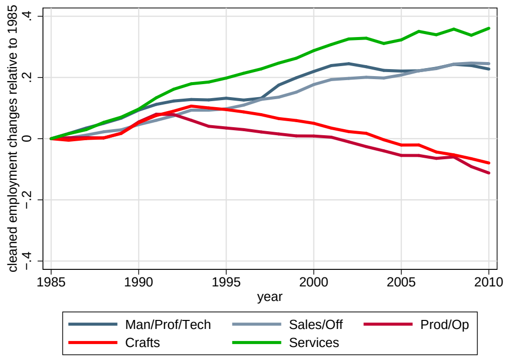


Figure 15: Wage percentiles over time, overall and percentiles of workers who just entered the profession.



(a) Overall polarization



(b) Polarization due to switching from one period to next.

Figure 16: Influence of switching on polarization.

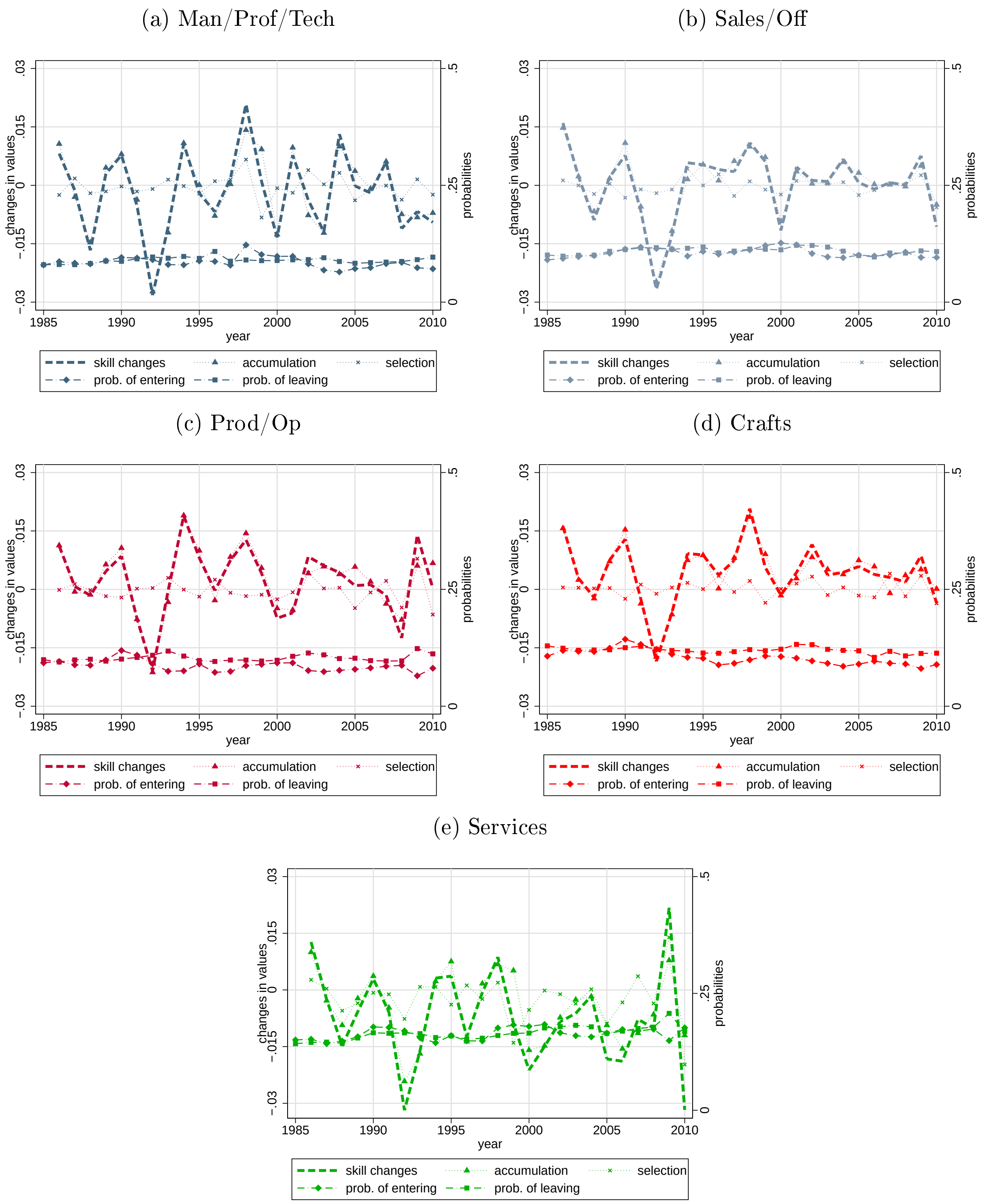


Figure 17: Incremental results for the decomposition of mean wage changes into prices and skills.

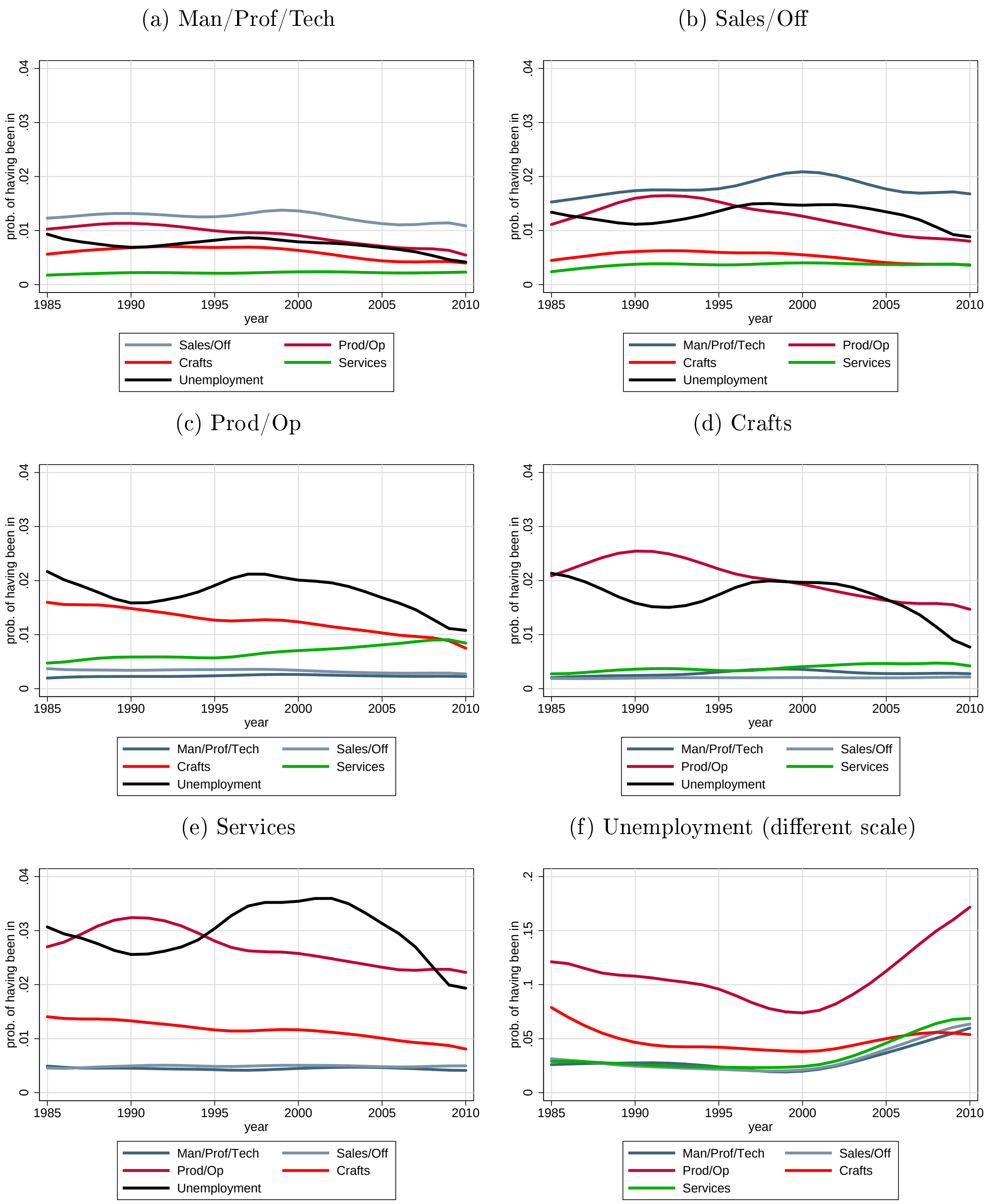


Figure 18: Share of switchers (new entrants) in each profession/unemployment over years.