Appendix Accompanying: Occupation Growth, Skill Prices, and Wage Inequality

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A Further Details on the Data and Empirical Facts

A.1 Dataset Construction

We employ the SIAB Scientific Use File for our analyses. The SIAB is a 2% random sample of administrative German social security records spanning the years 1975 until 2014.[1] It includes employees covered by social security, marginal part-time employment (since 1999), unemployment insurance benefit recipients, and individuals who are officially registered as job-seeking or who are participating in programs of active labor market policies. It excludes the self-employed, civil servants, individuals performing military service, and those not in the labor force. In total, it is representative for 80% of the German workforce.

Most notably, it contains an individual's full employment history, including a time-consistent occupational classifier (up to 2010), the corresponding wage, year of birth, place of work, and education. The data is exact to the day as employers need to notify the employment agency if the employment relationship changes. Therefore, the data is available in a spell structure making it possible to observe the same individual at various employers within a year. Those spells may even overlap as workers can have multiple employment contracts at a time. We transform the spell structure into a yearly panel by identifying the longest spell within a given year and deleting all the remaining spells. This procedure differs from the previous inequality literature employing the SIAB in the German context. For instance, Dustmann et al. (2009) aggregate all the information from various spells within a year, adding up all the earnings from multiple employment spells. Since our focus is on occupations, this is impossible to do as one cannot aggregate multiple categorical occupation information. Fortunately, the number of workers in our main sample with more than one spell in a year is negligible (< 1.3%) and so of minor concern.

A.1.1 Sociodemographics

Occupations: The detailed 120 occupations (KLDB1988) of our main analysis can be found in Table A.1. Some parts of the analysis make use of a grouping of these 120 occupations into four major classes in the spirit of Acemoglu and Autor (2011):

1. Managers-Professionals-Technicians (Mgr-Prof-Tech)
2. Sales-Office (Sales-Office)
3. Production-Operators-Craftsmen (Prod-Op-Crafts)
4. Services-Care (Srvc-Care)

[1] Access to the data is subject to signing a contract with the Research Data Center of the German Federal Employment Agency. See Ganzer et al. (2017) for an up to date documentation of the data. We carried out all the analyses making use of the templates provided by von Gaudecker (2019).

Education: The education variable contained in the SIAB suffers from some inconsistencies and missing values as described in Fitzenberger et al. (2006) because this information is not irrelevant for social security contributions. We use Fitzenberger et al.'s imputation to obtain an education variable with three or five distinct distinct outcomes: low (missing or without any postsecondary education), medium (apprenticeship training or high school diploma), and high (university degree).

Table A.1: Grouping of occupations

Group	SIAB occupation
Managers	Consultants, tax advisers
	Entrepreneurs, senior managers
	Members of Parliament, Ministers, elected officials until association leaders, officials
Professionals	Architects, civil engineers
	Artistic and performance occupations
	Chemists, chemical engineers until physicists, physics engineers, mathematicians
	Economic and social scientists, statisticians until scientists n.e.c.
	Electrical engineers
	Home wardens, social work teachers
	IT experts
	Journalists until librarians, archivists, museum specialists
	Mechanical, motor engineers
	Music teachers, n.e.c. until other teachers
	Musicians until scenery/sign painters
	Navigating ships officers until air transport occupations
	Physicians until Pharmacists
	Social workers, care workers until religious care helpers
	Soldiers, border guards, police officers until judicial enforcers
	Survey engineers, other engineers
	University teachers, lecturers at higher technical schools and academies until technical, vocational, factory instructors
Technicians	Biological specialists until physical and mathematical specialists
	Chemical laboratory assistants until photo laboratory assistants
	Electrical engineering and building technicians
	Foremen, master mechanics
	Measurement technicians until remaining manufacturing technicians
	Mechanical engineering technicians
	Other technicians
	Technical draughtspersons
Sales	Bank and building society specialists
	Commercial agents, travellers until mobile traders

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Table A.1: Grouping of occupations

Group	SIAB occupation
	Forwarding business dealers
	Health insurance specialists (not social security) until life, property insurance specialists
	Publishing house dealers, booksellers until service-station attendants
	Salespersons
	Tourism specialists, cashiers, ticket inspectors
	Wholesale and retail buyers
Office	Accountants, valuers
	Office auxiliary workers
	Office specialists
	Stenographers, shorthand-typists, typists until data typists
Production	Building laborer, building assistants
	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
	Goods examiners, sorters
	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)
	Machine operators
	Metal grinders until other metal-cutting occupations
	Metal polishers until metal bonders and other metal connectors
	Metal workers
	Metal workers (no further specification)
	Miners until shaped brick/concrete block makers
	Other assemblers
	Packagers, goods receivers, despatchers
	Paper product and cellulose makers
	Paviors until road makers
	Plant fitters, maintenance fitters until steel structure fitters, metal shipbuilders
	Plastics processors

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Table A.1: Grouping of occupations

Group	SIAB occupation
	Sheet metal pressers, drawers, stampers until other metal moulders (non-cutting deformation)
	Special printers, screeners
	Spinners, fibre preparers until skin processing operatives
	Steel smiths until pipe, tubing fitters
	Tracklayers until other civil engineering workers
	Turners
	Type setters and printers
	Welders, oxy-acetylene cutters
	Wood preparers until basket and wicker products makers
Operators	Assistant laborers
	Motor vehicle drivers
	Post masters until telephonists
	Railway engine drivers until street attendants
	Stowers, packers, stores/transport workers
	Transportation equipment drivers
	Warehouse managers, warehousemen
Craftsmen	Agricultural machinery repairers until precision mechanics
	Bakery goods makers until confectioners (pastry)
	Bricklayers, 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
	Painters, lacquerers (construction)
	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
	Wine coopers until sugar, sweets, ice-cream makers
Service	Bar keepers, waiters, stewards

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Table A.1: Grouping of occupations

Group	SIAB occupation
	Cashiers
	Cooks
	Doormen, caretakers until domestic and non-domestic servants
	Factory guards, detectives until watchmen, custodians
	Hairdressers until other body care occupations
	Household and buildings cleaners
	Housekeeping managers until employees by household cheque procedure
	Laundry workers, pressers until textile cleaners, dyers and dry cleaners
	Others attending on guests
	Street cleaners, refuse disposers until machinery, container cleaners and related occupations
Care	Dietary assistants, pharmaceutical assistants until medical laboratory assistants
	Medical receptionists
	Non-medical practitioners until masseurs, physiotherapists and related occupations
	Nursery teachers, child nurses
	Nurses, midwives
	Nursing assistants

A.1.2 Wages and Wage Growth

Despite being accurately measured as the employer can be punished for incorrect reporting, the contained wage variable has two major drawbacks for our analysis.

Wage imputations: First, wages are top coded, amounting to roughly 12% censored observations for men and 2.4% censored observations for women on average across years in our main sample. We impute top coded wages using a series of tobit imputations as in Dustmann et al. (2009) or Card et al. (2013), fitted separately for each year, gender and East-West region. We predict the upper tail of the wage distribution employing controls for five age groups and five education groups as well as their interaction and allow the error variance to vary between age and education groups. Further, we include controls for age (within age groups), a part-time dummy, 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 as in Card et al. (2013).[2] 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 $u \sim U[0,1]$, $k = \Phi[(c - X'\hat{\beta})/\hat{\sigma}]$ and c is the main censoring limit.[3] Analogous to Jäger and Heining (2019) we scale up daily to yearly

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

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

wages by multiplying with 365. We inflate wages to prices as of 2010 and finally smooth wages for every individual using three year moving averages.[4]

Wage break 1983/1984: The second major concern with the wage variable is that the definition of a wage – relevant for social security payments – changed between 1983 and 1984. Prior to 1984, wages did not contain bonuses and one time payments. Afterwards these variable parts of the wage were included. If one does not correct this break, it leads to a spurious increase in inequality between those years. 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 not have changed much. Additionally, they control for the fact that different percentiles of the wage distribution should be differently affected by the break since workers from higher percentiles are likely to receive higher bonuses. Therefore, they estimate locally weighted regressions, separately for men and women, of an individual's wage ratio in 1983/1984 and 1983/1982 on the rank of a person in the wage distribution. Afterwards, they 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 this, 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 occupations. For instance, by employing this procedure, the amount of censored wages within the Mgr-Prof-Tech group aged $[45, 54]$ increases up to 66% in 1975. Instead of following that approach, we do not reset wages back to the censoring limit if they were corrected above the limit but leave them at their break corrected values. We create individual log wage growth as the log wage in year t minus the log wage in year $t-1$ and set it to missing if the worker was not observed in $t-1$.

A.1.3 Sample Selection

The main dataset is restricted to full time working 25 to 54 year old men. Since wages in the SIAB are reported as average daily earnings, the full-time restriction is as in Dustmann et al. (2009) or Card et al. (2013) to condition on similar working hours per day. We exclude younger workers so that the vast majority of our sample will have concluded their formal education by the time they enter our sample. We stop relatively early because early retirement programs were very common in Germany, particularly in the 1980s and 1990s. Additionally, we drop workers who left the sample for more than 10 years into non-participation, self employment, or the public sector. 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. 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. Furthermore, we drop all spells of workers who ever worked in East Germany as well as permanently foreign workers.[5] The main sample consists of 5,792,111 worker $\times$ year combinations with 428,326 unique workers. Dropping observations with missing information in $t-1$ results in 5,217,232 observations. The median worker

[4]Not smoothing wages does not change the results but leads to spikes in few small occupations.

[5]That is, workers who are German at some point but foreign at another, are not dropped from the sample. In robustness checks we include the dropped East Germans and foreigners.

born in the cohort 1950–1956 (the cohort we potentially observe from 25 to 54) is observed for 24 years.

A.1.4 Sample with Imputed Non-Employment Spells

One of our key robustness checks (Section D.2) concerns the role of unemployment and out of labor force spells. For this, we relax the exogeneity assumption for unemployment and out of labor force by imputing the occupation where the worker "would have worked in had he not become unemployed or left the labor force".[6] We do the imputation by comparing the (real) wage after a non-employment spell with the wage before the non-employment spell. We then impute the wage while in non-employment as the lower of those two wages adjusted for inflation and set the occupation within this time to the occupation that corresponds to that lower wage.[7] The rationale for this procedure is based on the idea that a worker could always choose the lower paying job but eventually decides to quit employment if he prefers becoming unemployed. Imputing unemployed and out of labor force spells results in 6,170,729 observations. Dropping observations with missing information in $t-1$ leaves us with 5,710,542 observations.

[6] Between 1996 and 1998, many workers in occupation 102 "Physicians until Pharmacists" exit the sample and return afterwards as mentioned by Ganzer et al. (2017). We impute those likely erroneously missing observations by setting the occupation to 102 if a worker was in 102 in 1995 and returned in 1999 or 2000 and linearly interpolate the missing wage using the observations in 1995 and 1999/2000. We also drop workers in that group with very low wages between 1988 and 2004 ("Arzt im Praktikum").

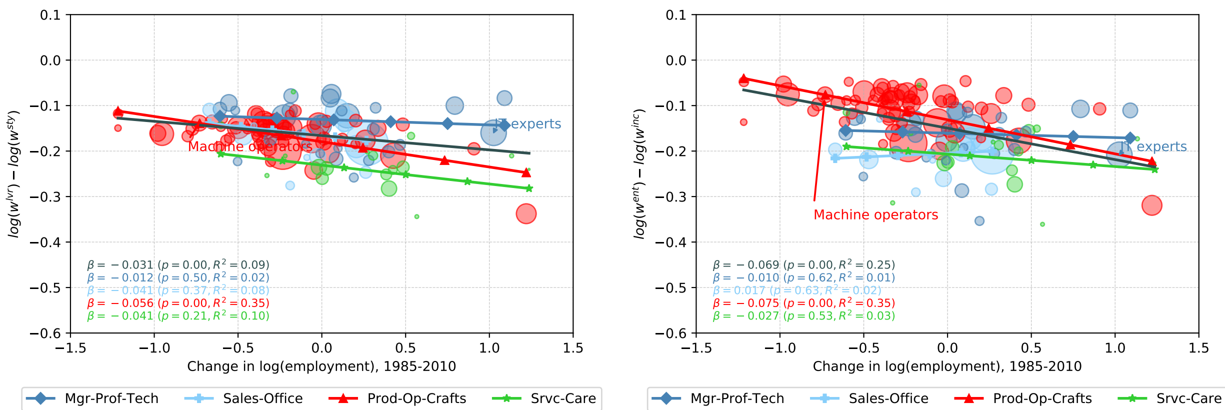
[7] As we only fill up spells *between* two employment spells, we therefore treat both unemployment and permanently leaving the labor force without returning to employment as exogenous actions.

A.2 Additional Stylized Facts

Figure A.1: Selection into and out of occupations, controlling for interactions in year × education × age

(a) Entrants' minus incumbents' wages

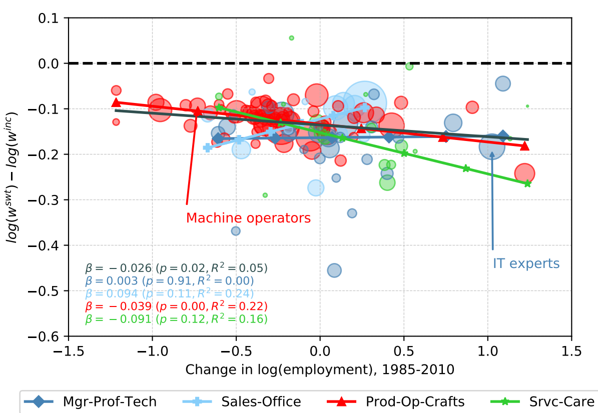
(b) Leavers' minus stayers' wages



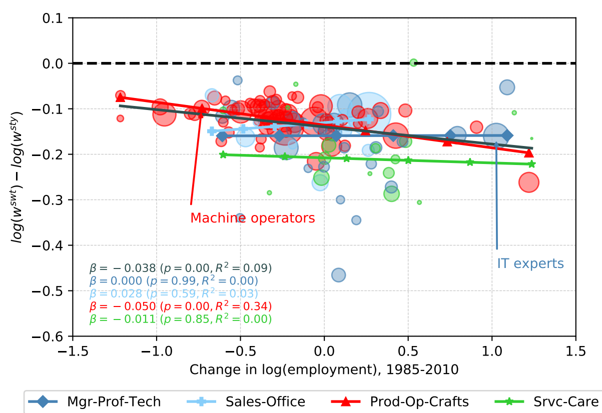
Notes: The vertical axis in Panel A.1a shows the residual wage of an entrant to an occupation relative to the average wage of incumbents after a regression on the interaction of dummies for calendar year, education (no postsecondary, Abitur or apprenticeship, and university degree), and years of age. The average is taken across years 1985 until 2010. The vertical axis in Panel A.1b shows the residual wage of a worker leaving an occupation next period relative to the average wage of stayers after a regression on the interaction of dummies for calendar year, education, and years of age. The average is taken across years 1984 until 2009. The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure A.2: Selection into and out of occupations, occupational switchers only

(a) Entrant from occ. minus incumbents' wages



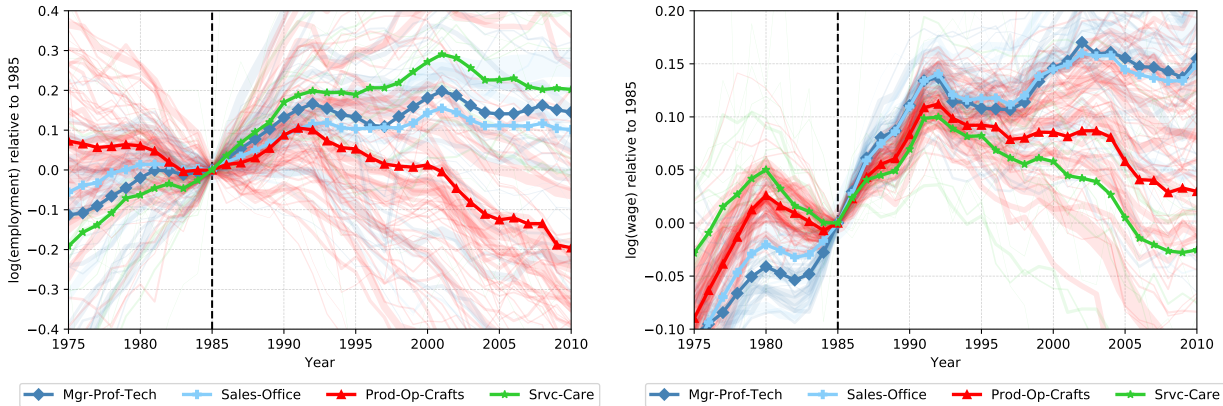
(b) Leaver to occ. minus stayers' wages



Notes: The vertical axis in Panel A.2a shows the average wage of an entrant to an occupation who switches from another occupation relative to the average wage of incumbents. The average is taken across years 1985 until 2010. The vertical axis in Panel A.2b shows the average wage of a worker leaving an occupation by switching to another occupation next period relative to the average wage of stayers. The average is taken across years 1984 until 2009. The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure A.3: Changes in employment and average wages, 1975-2010

(a) Relative employment (b) Relative Wages



Notes: Panel A.3a shows the log number of workers employed in occupations over time. Panel A.3b shows the log wage of workers employed in occupations over time. Shaded lines in the background represent the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. The thickness of a shaded background line corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010.

A.3 Switching probabilities as in Groes et al. (2014)

Figure A.4: Probability to Leave by Wage Rank within Occupation

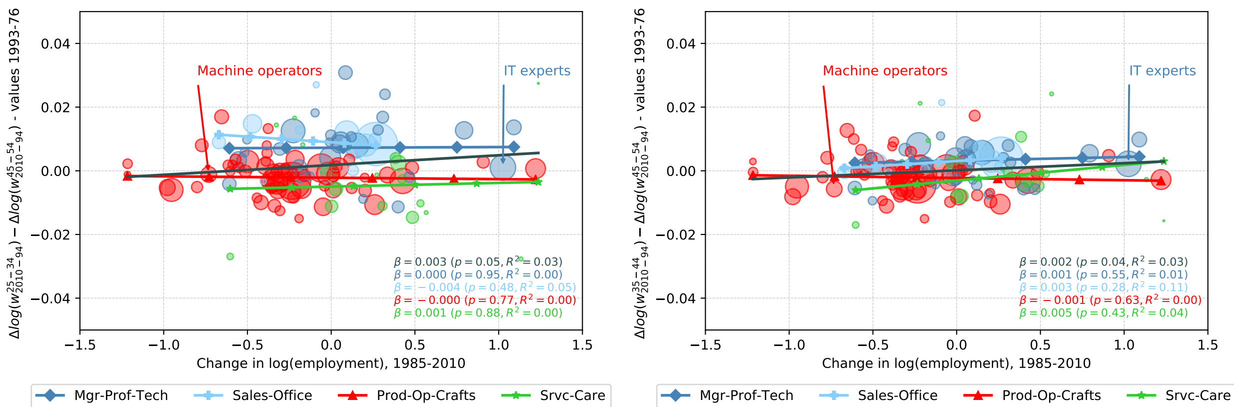
Notes: The line shows the average probability to switch occupations based on a worker's percentile in the origin occupation. We group the SIAB-SUF data by occupation and year, calculate percentiles, and generate the probability of switching based on this percentile.

A.4 Constancy of Skill Accumulation

Figure A.5: Wage growth between age groups

(a) [25, 34] year olds - [44, 54]

(b) [35, 44] year olds - [44, 54]



Notes: The figures show a triple difference-in-difference result: how much has wage growth of young (Figure A.5a) and middle-aged (Figure A.5b) workers relative to the wage growth of old workers changed after 1993 relative to pre 1993? One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

The figure shows a triple difference-in-difference result: how much has wage growth of young and middle-aged workers relative to the wage growth of old workers changed after 1993 relative to pre 1993? Ideally, the y coordinates of all points would have been close to zero. Despite this not being exactly the case, still 80% of the occupations have absolute differences in growth rates below one percentage point for the 25-34 vs 45-54 comparison; the same holds for 95% of the sample in the 35-44 vs. 45-54 comparison. Importantly, we cannot detect any systematic pattern and there is no clear relation with employment growth, neither overall nor within the four occupation groups. There is one prominent outlier with a very large positive difference. These are medical doctors, who had very high growth rates between 1998 and 2004, a period when low-paid residencies were mandatory for their approbation ("Arzt im Praktikum").

B Theory

B.1 A K-Sector Roy Model with Random Skills

We sketch a static Roy model based on Hsieh et al. (2019), which can rationalize our stylized facts in Figures 2 and 3. The simplest version of the random skills model in Hsieh et al., adapted to our notation, is where individuals' wage level in occupation k is given by $W_{i,t,k} = \Pi_{t,k} S_{i,t,k}$ and skills are drawn from a multivariate Fréchet distribution.[8] Then, employment shares of each occupation become (Proposition 1 in Hsieh et al., 2019):

$$p_{t,k} = \frac{\Pi_{t,k}^{\theta}}{\sum_{k=1}^{K} \Pi_{t,k}^{\theta}}, \tag{1}$$

where the Fréchet parameter θ governs the dispersion of skills. Per Proposition 2 in Hsieh et al. (2019), average skills in k become:

$$E[S_{i,t,k}] = \Lambda p_{t,k}^{-\frac{1}{\theta}} = \Lambda \frac{\left(\sum_{k=1}^{K} \Pi_{t,k}^{\theta}\right)^{1/\theta}}{\Pi_{t,k}}, \tag{2}$$

where Λ is a constant that captures various factors common across occupations. Equation (2) shows that in this model, average wages $\Pi_{t,k} E[S_{i,k}]$ relative to other occupations neither depend on the occupation's skill price nor on its employment share. The latter is exclusively a function of the skill price. Differentiating $E[S_{i,t,k}]$ with respect to $p_{t,k}$,

$$\frac{\partial E[S_{i,t,k}]}{\partial p_{t,k}} = -\Lambda \frac{1}{\theta} p_{t,k}^{-\frac{1}{\theta}-1} < 0 \tag{3}$$

shows that occupation entrants and leavers are always lower-skilled than incumbents and stayers. Also, the more an occupation grows, the larger this skill difference, since (3) declines monotonically. Hsieh et al. (2019) further allow for schooling decisions and homogeneous returns to experience. While the second is always neutral, the first would in principle raise the correlation of skills across occupations. However, occupational choices depend on the individual skill endowments from the Fréchet and workers never switch occupations during their career. Essentially, this is thus a static Roy model with uncorrelated skill endowments.

The model (1)–(3) captures the empirical facts in Figures 2–3 well in the sense that marginal workers are indeed lower-skilled than inframarginal workers in all occupations,[9] and that occupational employment growth is not correlated with wage growth. Hsieh et al. (2019) also find that the latter is the case in their US-CPS data (i.e., their Figures 8–10). An alternative to this is the standard two-sector Roy model (e.g., Heckman and Taber, 2010), where sufficiently low correlation of normally distributed skills also yields positive selection into both occupations. This is very hard to solve analytically with multiple sectors, but Gould (2002) finds in a structural estimation that a

[8] These are ex ante skills before occupation choice (and schooling in the full Hsieh et al. (2019) model), and the Fréchet assumption imposes that they are uncorrelated across occupations.

[9] The slopes in Table 1 further show that these differences increase in occupations' employment growth.

split of the U.S. economy into professional, blue collar, service jobs also yields positive selection in all three occupations.

What these static models miss is the role of skill changes over the career. They arguably capture differences in skill endowments, which are important but typically the smaller component of our eventual results. Once they have entered an occupation, workers' skills are likely to become increasingly specific over time. Table 2 shows that skill accumulation strongly contributes to negative growth selection. At the same time, individuals who stay in their chosen occupations are positively selected also on idiosyncratic shocks, which again matters in Table 2.

B.2 A Tractable Model of Sector Choice

Here we describe our framework based on Böhm (2020) in more detail. There are $k = 1, \dots, K$ distinct occupations. At time t a worker i earns potential wages $W_{i,t} = \begin{pmatrix} W_{i,t,1} & W_{i,t,2} & \dots & W_{i,t,K} \end{pmatrix}$. Most of our analysis will be in relative terms and we use lowercase letters to denote the logarithm of a variable. As in Roy (1951), we assume that workers maximize their incomes by choosing the occupation in which they earn the highest wage:

$$w_{i,t} = \max\{w_{i,t,1}, \dots, w_{i,t,K}\} = w_{i,t,k(i,t)}, \tag{4}$$

where the occupation subscript's argument (i, t) again indicates that k is i's choice in time t. As we alluded we can write the change of the wage between $t-1$ and t as:

$$\begin{aligned} \Delta w_{i,t} &= w_{i,t,k(i,t)} - w_{i,t-1,k(i,t-1)} \\ &= \left(w_{i,t,k(i,t)} - w_{i,\tau*,k(i,t)}\right) - \left(w_{i,\tau*,k(i,t-1)} - w_{i,t-1,k(i,t-1)}\right) \end{aligned} \tag{5}$$

That is, equation (5) notionally decomposes the gain in wages when the worker is already in his new occupation $k(i, t)$ plus the gain when he is still in the old occupation $k(i, t-1)$, where at the switch point he is exactly indifferent such that the relative wage in the two sectors is zero (i.e., $w_{i,\tau*,k(i,t)} - w_{i,\tau*,k(i,t-1)} = 0$).

We know from the worker's maximizing behavior (4) that $w_{i,t-1,k(i,t-1)} - w_{i,t-1,k(i,t)} \geq 0$ and $w_{i,t,k(i,t-1)} - w_{i,t,k(i,t)} < 0$ such that the indifference point must be somewhere in between

$$(1-\lambda)\left(w_{i,t-1,k(i,t-1)} - w_{i,t-1,k(i,t)}\right) + \lambda\left(w_{i,t,k(i,t-1)} - w_{i,t,k(i,t)}\right) = 0,$$

with $\lambda \in [0, 1)$. Our Assumption 1 is that this is exactly in the middle and $\lambda = 1/2$. Inserting Assumption 1 (i.e., a term that is zero but can be used to rewrite the equation) into (5) we get Result 1:[10]

[10]We could make other assumptions on λ that could also be empirically implemented. Using Monte Carlo simulations, Böhm and von Gaudecker (2021) find that the $\lambda = 1/2$ of Assumption 1 appears to be a very good approximation in practice.

$$
\begin{aligned}
\Delta w_{i,t} &= w_{i,t,k(i,t)} - w_{i,t-1,k(i,t-1)} \\
&\quad + \frac{1}{2}\Big(\big(w_{i,t-1,k(i,t-1)} - w_{i,t-1,k(i,t)}\big) + \big(w_{i,t,k(i,t-1)} - w_{i,t,k(i,t)}\big) \Big) \\
&= \frac{1}{2}\big(w_{i,t,k(i,t)} - w_{i,t-1,k(i,t)}\big) + \frac{1}{2}\big(w_{i,t,k(i,t-1)} - w_{i,t-1,k(i,t-1)}\big) \\
&= \frac{1}{2}\big(\Delta w_{i,t,k(i,t)} + \Delta w_{i,t,k(i,t-1)}\big)
\end{aligned}
\tag{6}
$$

This is useful because we have now rewritten the definition of the worker's wage growth in terms of quantities that we want to estimate (i.e., the changes in potential wages) and observables (i.e., the choices indicated by $k(i,t), k(i,t-1)$).

The intuition for Assumption 1 is that, while individual workers can become indifferent at various points in the $[w_{i,t-1,k(i,t-1)} - w_{i,t-1,k(i,t)}, w_{i,t,k(i,t-1)} - w_{i,t,k(i,t)})$ interval, on average (conditional on every switch type) this should appromiately happen in the middle. A related intuition and more extensive discussion can be found in Böhm (2020). Expanding on decomposition (5), he expresses $\Delta w_{i,t}$ as a function of the whole path of a worker's choices and wages within the period $[t-1,t)$.[11] He then again obtains the result (6) by linearly interpolating the incremental change in the choice indicators for $k(i,t), k(i,t-1),$.

B.3 Multidimensional as Opposed to One-Dimensional Skills

The easiest way to reject the one-dimensional skill model is to note that the sector-specific wage distributions overlap, e.g., that there exist Mgr-Prof-Tech workers who earn less than some Srvc-Care workers. In the one-dimensional skill model this is impossible because there is a ranking of skill cutoffs above each of which the worker moves to a higher-ranked occupation.

However, the focus of our paper is not in levels of skills but changes of skills and their prices. Therefore, the question is rather whether workers' skill may be described without loss of generality as changing one-dimensionally over the career. This is explored in the following.

B.3.1 Theory: Wage Gains When Switching Between Sectors

The multidimensional Roy model postulates $w_{i,t,k} = \pi_{t,k} + s_{i,t,k}$ as opposed to a one-dimensional skill model a la Cortes (2016) or Acemoglu and Autor (2011), $w_{i,t,k} = \pi_{t,k} + \beta_k \mathfrak{s}_{i,t}$ with $\mathfrak{s}_{i,t}$ a general skill that is priced differently in different sectors according to β_k. The multidimensional skill *change* model flexibly states $\triangle w_{i,t,k} = \triangle \pi_{t,k} + \triangle s_{i,t,k}$ while the one-dimensional skill change model has the restriction: $\triangle w_{i,t,k} = \triangle \pi_{t,k} + \beta_k \triangle \mathfrak{s}_{i,t}$. This implies that there may be increasing and concave life-cycle profiles of workers in the one-dimensional skill model, idiosyncrasy among these profiles when different workers obtain different shocks, and systematic heterogeneity in the data depending on whether workers switch into more high-skilled sectors (i.e., sectors with a higher skill return β_k) or not. Nonetheless, even in the most general form of this one-dimensional model there are some quite strong empirical restrictions, which we derive now.

[11] Böhm (2020) also discusses cases where during $[t-1,t)$ workers switch from $k(i,t-1)$ to a third occupation before finally moving to $k(i,t)$. This is more of a concern for his comparison of task price changes across two decades than for our one-year period length here.

To simplify for the moment we continue with constant skill prices $\triangle\pi_k = 0$ and we drop the individual index i. We reintroduce subscript k to $\mathfrak{s}_{k,t}$, which now denotes only the choice at time t, since skills are assumed general (homogeneous across sectors) for the rest of this section. The skill in t for a worker who moved from k' in $t-1$ to k in t is denoted by $\mathfrak{s}_{k'\to k,t}$.

With this notation, suppose a worker starts in sector k with skill $\mathfrak{s}_{k,t-1}$ and stays there or switches either to sector k' or k'' with $\beta_{k''} > \beta_{k'} > \beta_k$. In order to have non-zero employment in all three sectors, we need that $\pi_k > \pi_{k'} > \pi_{k''}$. Therefore, k'' is the highest skill return and skilled sector.[12] Define the conditions for the choices:

- $k \to k$: if $\pi_k + \beta_k\mathfrak{s}_{k,t-1} > \pi_{k'} + \beta_{k'}\mathfrak{s}_{k,t-1} > \pi_{k''} + \beta_{k''}\mathfrak{s}_{k,t-1}$ and $\pi_k + \beta_k\mathfrak{s}_{k\to k,t} > \pi_{k'} + \beta_{k'}\mathfrak{s}_{k\to k,t} > \pi_{k''} + \beta_{k''}\mathfrak{s}_{k\to k,t}$. Wage gain: $\triangle w_{k\to k} = \beta_k(\mathfrak{s}_{k\to k,t} - \mathfrak{s}_{k,t-1})$.
- $k \to k'$: if $\pi_k + \beta_k\mathfrak{s}_{k,t-1} > \pi_{k'} + \beta_{k'}\mathfrak{s}_{k,t-1} > \pi_{k''} + \beta_{k''}\mathfrak{s}_{k,t-1}$ and $\pi_{k'} + \beta_{k'}\mathfrak{s}_{k\to k',t} > \pi_k + \beta_k\mathfrak{s}_{k\to k',t}$ plus $\pi_{k'} + \beta_{k'}\mathfrak{s}_{k\to k',t} > \pi_{k''} + \beta_{k''}\mathfrak{s}_{k\to k',t}$. Wage gain: $\triangle w_{k\to k'} = \beta_{k'}\mathfrak{s}_{k\to k',t} - \beta_k\mathfrak{s}_{k,t-1}$.
- $k \to k''$: Wage gain: $\triangle w_{k\to k''} = \beta_{k''}\mathfrak{s}_{k\to k'',t} - \beta_k\mathfrak{s}_{k,t-1}$.

Since the skill levels have to be $\mathfrak{s}_{k\to k'',t} > \mathfrak{s}_{k\to k',t} > \mathfrak{s}_{k\to k,t}$ for the choices in t to be optimal and $\beta_{k''} > \beta_{k'} > \beta_k$ we have a clear ranking of wage gains that we should observe in the data: $\triangle w_{k\to k''} > \triangle w_{k\to k'} > \triangle w_{k\to k}$.

For one origin occupation k (Srvc-Care, say) this is unrestrictive because we can use the observed gains to rank the sectors, i.e., to infer that $\beta_{k''} > \beta_{k'} > \beta_k$ and $\pi_k > \pi_{k'} > \pi_{k''}$ needs to be the case. Using additional origin occupations, k'' (Mgr-Prof-Tech) this does become a restriction as the one-dimensional skill model for a given skill (wage) $\mathfrak{s}_{k'',t-1}$ now prescribes the same ranking in terms of wage gains by destination:

$$\triangle w_{k''\to k''} = \beta_{k''}\mathfrak{s}_{k''\to k'',t} - \beta_{k''}\mathfrak{s}_{k'',t-1} > \triangle w_{k''\to k'} = \beta_{k'}\mathfrak{s}_{k''\to k',t} - \beta_{k''}\mathfrak{s}_{k'',t-1} >$$

$$> \triangle w_{k''\to k} = \beta_k\mathfrak{s}_{k''\to k,t} - \beta_{k''}\mathfrak{s}_{k'',t-1},$$

since $\mathfrak{s}_{k''\to k'',t} > \mathfrak{s}_{k''\to k',t} > \mathfrak{s}_{k''\to k,t}$ for the choices in t to be optimal and $\beta_{k''} > \beta_{k'} > \beta_k$. Similarly, we expect in the data that $\triangle w_{k'\to k''} > \triangle w_{k'\to k'} > \triangle w_{k'\to k}$. We can also condition on the destination sector. Fixing k with skill $\mathfrak{s}_{k,t}$ we get

$$\triangle w_{k\to k} = \beta_k\mathfrak{s}_{k,t} - \beta_k\mathfrak{s}_{k\to k,t-1} > \triangle w_{k'\to k} = \beta_k\mathfrak{s}_{k,t} - \beta_{k'}\mathfrak{s}_{k'\to k,t-1} > \triangle w_{k''\to k} = \beta_k\mathfrak{s}_{k,t} - \beta_{k''}\mathfrak{s}_{k''\to k,t-1},$$

since $\mathfrak{s}_{k\to k,t-1} < \mathfrak{s}_{k'\to k,t-1} < \mathfrak{s}_{k''\to k,t-1}$ for the choices in $t-1$ to be optimal and $\beta_{k''} > \beta_{k'} > \beta_k$. Similarly, $\triangle w_{k\to k'} > \triangle w_{k'\to k'} > \triangle w_{k''\to k'}$ and $\triangle w_{k\to k''} > \triangle w_{k'\to k''} > \triangle w_{k''\to k''}$.

We therefore obtain the following empirical restrictions from the one-dimensional (general as opposed to specific) skill model:

1. For any given origin sector k' and skill $\mathfrak{s}_{k',t-1}$, there is a fixed ranking of wage gains by destination sector. That is, the size ordering of wage gains $\{\triangle w_{k',1}, ..., \triangle w_{k'\to k}, ..., \triangle w_{k'\to K}\}$ does not depend on k'.

[12] These considerations directly follow Cortes (2016). He also shows that there exist unique cutoffs $\mathfrak{s}'$ and $\mathfrak{s}''$ determined by indifference that span mutually exclusive and exhaustive intervals $(-\infty, \mathfrak{s}']$, $(\mathfrak{s}', \mathfrak{s}'']$, and $(\mathfrak{s}'', \infty]$ of skills within which individuals choose work in k, k', and k'', respectively.

2. For any given destination sector k' and skill $\mathfrak{s}_{k',t}$, there is a fixed ranking of wage gains by origin sector. That is, the size ordering of wage gains $\{\triangle w_{1,k'}, ..., \triangle w_{k \to k'}, ..., \triangle w_{K,k'}\}$ does not depend on k' and it is exactly the inverse ordering of (1.), the ordering of destination sectors, in the running index $1, ..., K$.

We have abstracted from changes of skill prices in this argument. If sectors' skill intensities and wage ranks do not invert, i.e., the qualitative ranking $\beta_{k''} > \beta_{k'} > \beta_k$ and $\pi_k > \pi_{k'} > \pi_{k''}$ remains stable over time, which is strongly supported in the data, evolving skill prices do not affect the above results. The reason is again by revealed preference: conditioning on the same origin sector and skills, in order for his decision to be optimal, a worker switching into k'' has to have higher skill gains than a worker switching into k'. Since the worker switching into k'' could always switch into k' and have higher wage gains than the worker who actually decides to switch into k', the former worker's realized wage gain must be higher than the latter. If sectors' skill intensities or wage ranks had inverted in the data, we could always condition on sub-periods of our sample where they did not do that. Therefore, the empirical restrictions (1.) and (2.) from the one-dimensional skill model persist for the case of generally evolving skill prices over time.

A couple more features to notice:

- These restrictions do not depend on whether the skill changes arise from average accumulation or idiosyncratic deviations. The distribution of deviations/shocks does also not have to be known and can differ conditional on origin or destination sector. The key assumption that generates the restrictions is that the skill accumulation or shocks are general (one-dimensional), not sector specific!

- This model does not restrict that workers can learn more in some sectors than in others, e.g., that skill growth in Mgr-Prof-Tech is *on average* larger than in Srvc-Care. It is just that all skill growth is general (one-dimensional), not specific.

- One very helpful feature here is also that we can condition on the wage in the origin (1.) or destination (2.) sector and thus perfectly fix the worker's initial $\mathfrak{s}_{k',t-1}$ or final skill, since skills are indeed the same in each sector!

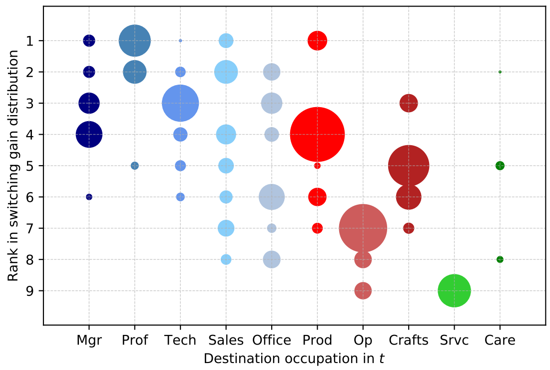
B.3.2 Evidence: Gains from Switching Into or Out of Ten Broad Occupations

Figure B.1a shows the rank of unconditional wage gains by each out of ten broad destination occupations. Restriction (1.) of the one-dimensional skill model predicts that there is a consistent ranking of these wage gains regardless of the origin occupations. We have already pre-ordered them using some prior knowledge and we see some of this in the figure, whereby wage gain ranks decline from the top-left of the graph to the bottom-right. In particular, workers moving into Mgr or Prof occupations tend to have highly ranked wage gains whereas workers moving into Srvc or Care occupations have among the lowest wage gains.

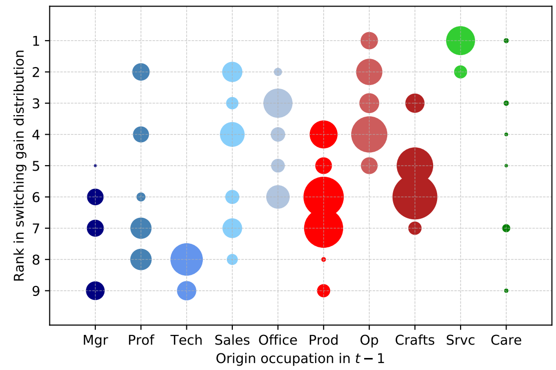
However, there is also a substantial amount of heterogeneity in these wage gain ranks. For example, it really depends on where a worker starts out from whether he has highly ranked wage gains moving into Sales or Office occupations, ranging from top gains (bubble at 1) to almost bottom (bubble at 8). Specifically, the highest gains of switching into Sales are for Prof and Office (bubbles at 1 and 2), while three out of the four lowest ranked gains are for the Prod, Op, or Crafts occupations. This makes sense if we think that workers acquire *relatively* little Sales-relevant skills

Figure B.1: Gains from switching

(a) Rank as a destination occupation



(b) Rank as an origin occupation



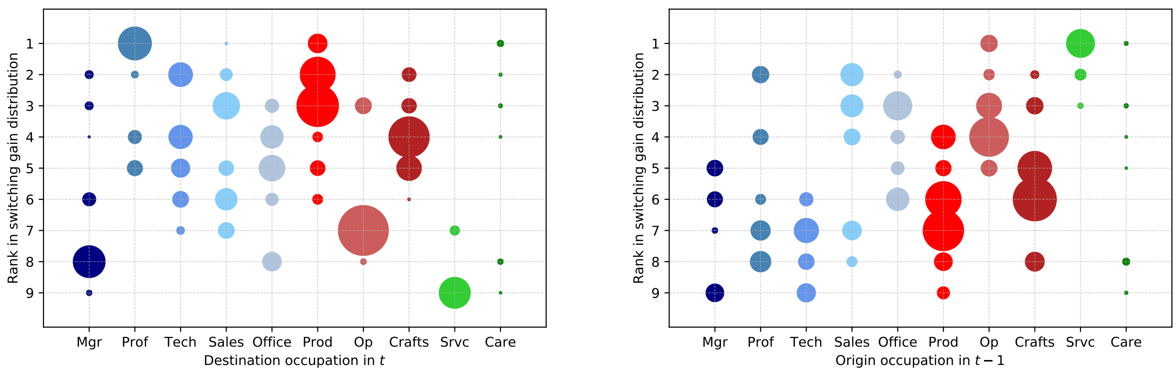
Notes: The ten groups are based on an aggregation of detailed occupations in the SIAB SUF as described in Appendix Table A.1. Bubbles show the rank (1 is highest, 9 is lowest) of an occupation in the distribution of average wage gains from switching. Bubble size corresponds to the amount of switchers. Panel B.1a shows the rank in (unconditional) wage gains from all occupations when the one on the x-axis is the destination occupation. Panel B.1b shows the rank in (unconditional) wage gains into all occupations when the one on the x-axis is the origin occupation.

(e.g., communication and persuasion) when working in Prod-Op-Crafts occupations, or if workers who choose Prod-Op-Crafts were initially endowed with relatively little Sales skills. In contrast, Tech is a high-gain destination for Prod-Op-Crafts workers (bubbles at 2 and 3) whereas Sales and Office (bubbles at 4 and 5) have lower gains moving into Tech. These different rankings of gains can also broadly be seen in our estimated skill accumulation Table C.1 below, and they reflect the fact that workers in different occupations have different specific skills.

Figure B.1b shows the inverse graph to what we just discussed, that is, the wage gains by origin occupations. Restriction (2.) of the one-dimensional skill model predicts that those are also consistently ranked and that the ranking is the inverse of the wage gains by destination. Indeed, we see that the gains in Figure B.1b tend to rise from the bottom left to top right inversely to Figure B.1a, and they tend to be lowest for workers moving out of Mgr-Prof-Tech occupations and highest for switchers out of Srvc and Care. However, we would expect the gains/losses from switching to be consistently ranked, i.e., movers out of Mgr having always the highest losses for all destination occupations, professionals always having the second-highest losses, up until workers leaving Srvc having the highest gains no matter what is the destination occupation. This is clearly not the case in Figure B.1b as there is again a substantial amount of heterogeneity in ranks depending on the destination and in fact in all of the ten occupations other than Srvc.[13] The gains are also far from perfectly inverted.

Figure B.2: Gains from switching (residual)

(a) Rank as a destination occupation (b) Rank as an origin occupation



Notes: The ten groups are based on an aggregation of detailed occupations in the SIAB SUF as described in Appendix Table A.1. Bubbles show the rank (1 is highest, 9 is lowest) of an occupation in the distribution of average wage gains from switching. Bubble size corresponds to the amount of switchers. Panel B.2a shows the rank in residual wage gains from all occupations when the one on the x-axis is the destination occupation. The residual wage growth holds origin wages constant, i.e., the residual from a regression of $\Delta w_{i,t}$ between t and $t-1$ on a worker's previous wage in $t-1$. Panel B.2b shows the rank in residual wage gains into all occupations when the one on the x-axis is the origin occupation. The residual wage growth holds destination wages constant, i.e., the residual from a regression of $\Delta w_{i,t}$ between t and $t-1$ on a worker's current wage in t.

The results we just discussed are qualitatively the same when controlling for wage in the origin and destination occupations, respectively in Figure B.2's Panels a and b, as prescribed by the theory in the previous section. The dispersion of gains is in fact more heterogeneous. That is, conditioning on origin skill brings out even more that there are differing rankings of destination sectors by origin occupation. Conditioning on destination skill brings out even more that there are differing rankings of origin sectors by destination occupation. Both of these results point to skills that are specific for different origin-destination combinations.

When controlling for age and other observables (not depicted) the results are again the same. We therefore conclude from this evidence that the one-dimensional skill (change) model can be a reasonable approximation of wage gains in some circumstances but overall it is rejected in the data with its heterogeneity of wage gain ranks. This matters for our results in the paper because it generates the evidence for direct occupation switchers in Table C.3, and more broadly the fact in

[13]For example, the gains of Prof moving into Mgr or Tech (bubbles in Prof column at 7 and 8) are low while the gains of Prod (bubbles at 4 and 5) or Crafts (bubbles at 3 and 5) moving into those occupations are higher. This is consistent with the one-dimensional skill model where Prof are highly-ranked occupations, moving from which can hardly constitute an improvement, whereas Prod and Crafts are rather middle-ranked occupations. However, the gains of switching from Prof as an origin are rather dispersed; especially moving into Office (bubble at 2) or Sales (bubble at 4) are quite high. In contrast, Prod (bubbles at 5 and 9) or Crafts (bubbles at 6 and 7) as an origin occupation have among the lowest gains moving into Office and Sales. Again, this is consistent with Prof workers having *relatively* high skills in Sales and Office compared to, for example, Prod and Crafts workers.

Figure 3 that both entrants and leavers in any occupation earn less than the respective incumbents and stayers.

B.4 Derivation of Equation (9)

$$
\begin{aligned}
&\mathrm{E}[s_{k,i,t}|I_{k(i,t)}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k(i,t-1)}=1]= \\
&\quad \underbrace{\mathrm{E}[s_{k,i,t}|I_{k(i,t)}=1,I_{k(i,t-1)}=1]}_{\mathrm{E}[s^{incumb}_{k,i,t}]}\cdot\underbrace{P(I_{k(i,t-1)}=1|I_{k(i,t)}=1)}_{1-p^{ent}_{k,t}} \\
&\quad +\underbrace{\mathrm{E}[s_{k,i,t}|I_{k(i,t)}=1,I_{k(i,t-1)}=0]}_{\mathrm{E}[s^{ent}_{k,i,t}]}\cdot\underbrace{P(I_{k(i,t-1)}=0|I_{k(i,t)}=1)}_{p^{ent}_{k,t}} \\
&\quad -\Bigg(\underbrace{\mathrm{E}[s_{k,i,t-1}|I_{k(i,t-1)}=1,I_{k(i,t)}=1]}_{\mathrm{E}[s^{sty}_{k,i,t-1}]}\cdot\underbrace{P(I_{k(i,t)}=1|I_{k(i,t-1)}=1)}_{1-p^{lvr}_{k,t-1}} \\
&\quad\quad +\underbrace{\mathrm{E}[s_{k,i,t-1}|I_{k(i,t-1)}=1,I_{k(i,t)}=0]}_{\mathrm{E}[s^{lvr}_{k,i,t-1}]}\underbrace{P(I_{k(i,t)}=0|I_{k(i,t-1)}=1)}_{p^{lvr}_{k,t-1}}\Bigg).
\end{aligned}
\tag{7}
$$

First notice that period $t-1$ stayers are the same individuals as period t incumbents and define $\mathrm{E}[\Delta s^{incumb}_{k,i,t}]\equiv\mathrm{E}[s^{incumb}_{k,i,t}]-\mathrm{E}[s^{sty}_{k,i,t-1}]$. We can now combine the second and fourth as well as the third and fifth row of (7):

$$
\begin{aligned}
\mathrm{E}[s_{k,i,t}|I_{k(i,t)}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k(i,t-1)}=1]&=\left(1-p^{lvr}_{k,t-1}\right)\cdot\mathrm{E}[\Delta s^{incumb}_{k,i,t}]+\left(p^{lvr}_{k,t-1}-p^{ent}_{k,t}\right)\cdot\mathrm{E}[s^{incumb}_{k,i,t}] \\
&+p^{lvr}_{k,t-1}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)+\left(p^{ent}_{k,t}-p^{lvr}_{k,t-1}\right)\cdot\mathrm{E}[s^{ent}_{k,i,t}].
\end{aligned}
$$

This decomposes the skill change with growth-selection only of entrants:

$$
\begin{aligned}
\mathrm{E}\left[s_{i,t,k(i,t)}\right]-\mathrm{E}\left[s_{i,t-1,k(i,t-1)}\right]=&\underbrace{\left(1-p^{lvr}_{k,t-1}\right)\cdot\mathrm{E}[\Delta s^{incumb}_{k,i,t}]}_{\text{1. Skill accumulation of } t-1 \text{ stayers}} \\
&+\underbrace{p^{lvr}_{k,t-1}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\text{2. Churning of leavers: difference entrants in } t\text{, leavers after } t-1} \\
&+\underbrace{\left(p^{ent}_{k,t}-p^{lvr}_{k,t-1}\right)\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{incumb}_{k,i,t}]\right)}_{\text{3. growth-selection of entrants}}
\end{aligned}
\tag{8}
$$

The inverse way of factoring out

$$\mathrm{E}[s_{k,i,t}|I_{k(i,t)}=1]-\mathrm{E}[s_{k,i,t-1}|I_{k(i,t-1)}=1]=\left(1-p^{ent}_{k,t}\right)\cdot\mathrm{E}[\Delta s^{incumb}_{k,i,t}]-\left(p^{ent}_{k,t}-p^{lvr}_{k,t-1}\right)\cdot\mathrm{E}[s^{sty}_{k,i,t-1}]$$
$$+\,p^{ent}_{k,t}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)-\left(p^{lvr}_{k,t-1}-p^{ent}_{k,t}\right)\cdot\mathrm{E}[s^{lvr}_{k,i,t-1}],$$

yields the decomposition with growth-selection only of leavers:

$$\begin{aligned}\mathrm{E}\left[s_{i,t,k(i,t)}\right]-\mathrm{E}\left[s_{i,t-1,k(i,t-1)}\right]=\ &\underbrace{\left(1-p^{ent}_{k,t-1}\right)\cdot\mathrm{E}[\Delta s^{incumb}_{k,i,t}]}_{\text{1. Skill accumulation of } t \text{ incumbents}}\\ +\ &\underbrace{p^{ent}_{k,t}\cdot\left(\mathrm{E}[s^{ent}_{k,i,t}]-\mathrm{E}[s^{lvr}_{k,i,t-1}]\right)}_{\text{2. Churning of entrants: difference entrants in } t\text{, leavers after } t-1}\\ +\ &\underbrace{\left(p^{ent}_{k,t}-p^{lvr}_{k,t-1}\right)\cdot\left(\mathrm{E}[s^{lvr}_{k,i,t-1}]-\mathrm{E}[s^{sty}_{k,i,t-1}]\right)}_{\text{3. Growth-selection of leavers}}\end{aligned}\tag{9}$$

Adding (8) and (9) and dividing by 2 gives Equation (9).

Note that skill prices are the same for entrants/incumbents in t and for stayers/leavers in $t-1$. Also, our stylised facts establish that both summands in the second term of the growth-selection effect are negative (marginal workers' wages are lower than inframarginal workers' wages in all professions). Hence, knowing wages is enough to determine the sign of this second term; any particular estimate of skills only affects its magnitude.

C Further Results for main estimation

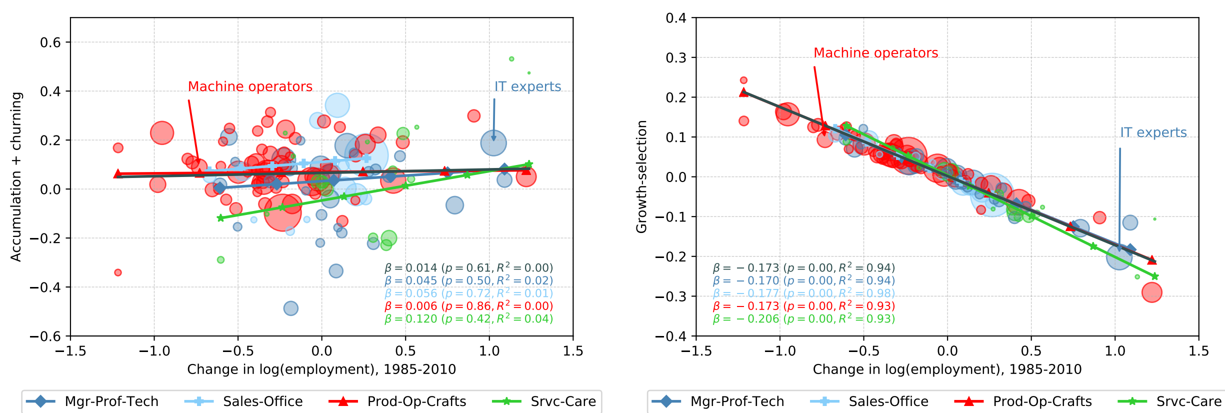
C.1 Skill Changes and the Growth-Selection Effect

This section reports additional details for the skill changes in occupations. Table C.1 reports the estimated average skill changes Γ for the four broad occupation groups. Figure C.1 shows the respective totals of accumulation and churning as well as growth-selection for entrants and leavers at the same time.

Note that the fact that the individual values for growth selection hew so close to the regression line is mechanical only to the extent that growth selection involves multiplication with net growth $p^{ent} - p^{lvr}$. Hence, the regression line passes through the origin. By definition, occupations with little changes in employment experience hardly any growth selection.

Figure C.1: Employment growth vs. the components of skill changes

(a) Accumulation + Churning (b) Growth-selection



Notes: Results correspond to sample averages following Equation (9). The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Table C.1: Estimated average skill changes (occupation groups)

			Age group		
Previous sector	Current sector		[25, 34]	[35, 44]	[45, 54]
Mgr-Prof-Tech	Mgr-Prof-Tech	γ	0.048	0.016	0.003
		σ_γ	0.000	0.000	0.000
	Sales-Office	γ	0.141	0.012	-0.034
		σ_γ	0.004	0.004	0.005
	Prod-Op-Crafts	γ	0.020	-0.048	-0.068
		σ_γ	0.005	0.005	0.006
	Srvc-Care	γ	-0.071	-0.124	-0.016
		σ_γ	0.011	0.012	0.016
Sales-Office	Mgr-Prof-Tech	γ	0.221	0.065	0.028
		σ_γ	0.003	0.004	0.005
	Sales-Office	γ	0.044	0.016	0.001
		σ_γ	0.000	0.000	0.000
	Prod-Op-Crafts	γ	0.125	0.042	-0.024
		σ_γ	0.004	0.005	0.007
	Srvc-Care	γ	-0.014	-0.117	-0.074
		σ_γ	0.010	0.012	0.015
Prod-Op-Crafts	Mgr-Prof-Tech	γ	0.206	0.117	0.073
		σ_γ	0.003	0.003	0.005
	Sales-Office	γ	0.088	0.059	0.008
		σ_γ	0.003	0.004	0.006
	Prod-Op-Crafts	γ	0.020	0.008	-0.007
		σ_γ	0.000	0.000	0.000
	Srvc-Care	γ	-0.071	-0.050	-0.019
		σ_γ	0.004	0.005	0.006
Srvc-Care	Mgr-Prof-Tech	γ	0.279	0.184	0.133
		σ_γ	0.009	0.011	0.016
	Sales-Office	γ	0.250	0.139	0.055
		σ_γ	0.008	0.011	0.015
	Prod-Op-Crafts	γ	0.300	0.220	0.123
		σ_γ	0.004	0.006	0.007
	Srvc-Care	γ	0.019	0.005	-0.011
		σ_γ	0.001	0.001	0.001

Notes: The table shows the estimated $\Gamma_{a,k,k}$, which represents skill accumulation for age a.The four groups are based on an aggregation of detailed occupations in the SIAB SUF as described in Appendix Table A.1. OLS estimates as described by Equation (6).

C.2 Sources of the Growth-Selection Effect

This section investigates the sources of growth-selection in more detail. We first describe details of our procedure to calculate the numbers in Table 2. We then highlight results from additional tables, which break down the growth selection effect in different ways.

Decomposition into endowments, accumulation, and shocks: In order to calculate the constituents of Equation (11) we employ the longitudinal information in the data to separate workers' skill endowment at the most recent entry from their predicted skill accumulation and idiosyncratic deviations during the stay in the current occupation. In particular, we write the skills of a worker i in occupation k as:

$$s_{i,t,k(i,t)} = s_{i,t_{i,0,k},k(i,t)} + \sum_{\tau=t_{i,0,k}}^{t-1} \Gamma_{a(i,t-1),k(i,t-1),k(i,t)} + \sum_{\tau=t_{i,0,k}+1}^{t} u_{i,\tau,k(i,t)}, \tag{10}$$

where the first term is the initial "endowment" when the worker entered this occupation at time $t_{i,0,k}$, the second term is predicted skill accumulation up to the current period t, and the last term are the cumulated estimated skill shocks in k since entry for this particular worker.[14] Notice that, as discussed in Section 3.2, the $\Gamma_{a,k,k}$s are ex post skill changes conditional on staying between $t-1$ and t. The shocks $u_{i,\tau,k(i,t)}$ are deviations from this, which differ systematically from the period-on-period average $\Gamma_{a,k,k}$ for workers who (endogenously) stay in an occupation for several periods.

Further empirical results on sources of growth-selection: Table C.2 reports our main decomposition into endowments, accumulation, and shocks by our usual three age groups: 25–34, 35–44, 45–54. This is just for completeness (results are not notably different), since in the main text we only show 25–34 and 35–54 for brevity.

Table C.3 reports the contributions to the growth-selection effect by origin and destination activities for entrants and leavers, respectively. The switches are between the broad professions, entry from (exit to) unemployment, temporary spells outside the labor market, and age-based labor market entry / sample exit at age 54.

Leavers to outside of the labor force have a fairly large effect everywhere, that is, a substantial amount of less-skilled workers are leaving all occupation groups in each period. Yet, entrants from outside the labor force exert a counteracting effect on growth-selection for the growing groups; they often enter from other forms of employment not covered in our data (self-employment, civil

[14] Strictly speaking, we do not know levels of skill prices and skills but we can compute i's overall accumulation $s_{i,t,k(i,t)} - s_{i,t_{i,0,k},k(i,t)} = w_{i,t,k(i,t)} - w_{i,t_{i,0,k},k(i,t)} - (\pi_{t,k(i,t)} - \pi_{t_{i,0,k},k(i,t)})$ and use $\sum_{\tau=t_{i,0,k}}^{t-1} \Gamma_{a(i,t-1),k(i,t-1),k(i,t)}$ to back out $\sum_{\tau=t_{i,0,k}+1}^{t} u_{i,\tau,k(i,t)}$ from (10). Then, for comparisons of entrants versus incumbents or leavers versus stayers at a given point in time, levels of skill prices and thereby level shifters of skills in the population cancel out.

Notice however that the empirical implementation of (10) is not invariant to the more general acceleration/deceleration interpretation of the skill price ($\Delta\hat{\pi}_{t,k} = \Delta\pi_{t,k} - \overline{\Delta\pi_{k,base}}$) and skill accumulation estimates ($\hat{\Gamma}_{a,k,k} = \Gamma_{a,k,k} + \overline{\Delta\pi_{k,base}}$ for stayers). The reason is that our calculations then give us $\hat{s}_{i,t,k} - \hat{s}_{i,t_{i,0,k},k} = s_{i,t,k} - s_{i,t_{i,0,k},k} + (t - t_{i,0,k})\overline{\Delta\pi_{k,base}}$ and $\sum_{\tau=t_{i,0,k}}^{t-1} \hat{\Gamma}_{a,k,k} = \sum_{\tau=t_{i,0,k}}^{t-1} \Gamma_{a,k,k} + (t - t_{i,0,k})\overline{\Delta\pi_{k,base}}$. Because the resulting $(t - t_{i,0,k})\overline{\Delta\pi_{k,base}}$ on each side of (10) cancel out, the idiosyncratic deviations term remains nonetheless unaffected.

servants, work abroad) and are high-skilled compared to incumbents. Experienced switchers (age 35–54) from Sales-Office to Mgr-Prof-Tech also have a negative growth-selection contribution, which could be due to progression within this given work context (Poletaev and Robinson, 2008). Leavers after age 54 also mostly exert a counteracting effect as they have accumulated substantial skills over their careers and they exit the sample for exogenous reasons. Overall, the majority of growth-selection in Table C.2 is accounted for by moves into or out of unemployment, the labor market, or the sample.

Nonetheless, switches between the broad professions do play a role, and more so in the growing and high-skill occupation groups: 32% of growth-selection in Mgr-Prof-Tech is due to between occupation group switches, 20% in Sales-Office, 4% in Prod-Op-Crafts, and 14% in Srvc-Care. In Appendix D.2 we repeat this analysis for our sample where we have filled non-employment spells using the wage and occupation of the adjacent spell with the lower wage. We find that the role of switches between occupations approximately doubles (there are still permanent entry and exit from the sample as alternative contributors). For completeness, Table C.4 reports the analysis by origin and destination activities for our usual three age groups

Finally, we analyze the growth-selection effect for some particularly interesting detailed occupations. In Table C.5 we decompose growth selection by the sources of skills. Mgr-Prof-Tech occupations overall experience growth-selection of -0.03 while the consultants / tax advisors and IT experts exhibit stronger declines of -0.115 and -0.202, respectively. Much of this is due to strong contributions of skill accumulation in these detailed professions. For cooks (-0.091 compared to -0.043 in its Srvc-Care group overall) endowments contribute a lot to negative growth selection, whereas for type setters / printers and machine operators (0.130 and 0.093 compared to 0.059 in their Prod-Op-Crafts group) skill shocks are particularly important. Accountants / valuers' and assistant laborers' employments move in the opposite directions of their respective Sales-Office and Prod-Op-Crafts occupation groups. This leads to positive growth-selection for shrinking accountants / valuers and strong negative growth-selection for growing assistant laborers.

In Table C.6 contributions of the main detailed origin and destination occupations for these professions are shown. We see that moves into or out of unemployment, the labor market, or the sample still account for most of growth selection but also that between-occupation switches have a substantial role to play (only exception being consultants / tax advisors).

Overall, there exists quite some heterogeneity across the particular detailed occupations on the magnitudes and drivers of growth selection. But the general picture is clear: Growing occupations experience declining skills and shrinking ones exhibit improving skill selection, with endowments, accumulation, and skill deviations all playing a substantial part.

Table C.2: Contributions to growth-selection by source of skills, 3 age groups

Source	Type	Age	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Endowment at the most recent entry into the occupation group	Entrants	25–34	0.196	0.188	0.096	0.238
		35–44	-0.029	-0.011	0.075	0.052
		45–54	-0.025	-0.018	0.043	0.035
	Leavers	25–34	0.158	0.158	0.084	0.218
		35–44	0.042	0.017	0.072	0.077
		45–54	-0.140	-0.101	0.054	0.021
Predicted **skill accumulation** since the most recent entry	Entrants	25–34	0.257	0.284	0.141	0.047
		35–44	0.091	0.075	0.058	0.016
		45–54	0.047	0.053	0.032	0.012
	Leavers	25–34	0.043	0.074	0.045	0.010
		35–44	0.005	0.004	0.023	-0.001
		45–54	0.120	0.137	0.027	0.058
Deviation of skills from the prediction since the most recent entry	Entrants	25–34	0.064	0.047	0.082	0.055
		35–44	0.022	0.011	0.034	0.017
		45–54	0.012	0.008	0.019	0.014
	Leavers	25–34	0.044	0.037	0.045	0.048
		35–44	0.063	0.035	0.057	0.030
		45–54	0.028	0.001	0.016	0.051
Background						
Growth Selection	Total		-0.030	-0.021	0.059	-0.043
Fractions	Entrants	25–34	0.620	0.636	0.667	0.574
		35–44	0.254	0.235	0.208	0.258
		45–54	0.126	0.130	0.124	0.169
	Leavers	25–34	0.234	0.299	0.300	0.375
		35–44	0.273	0.263	0.229	0.263
		45–54	0.492	0.438	0.471	0.362

Notes: This is the same decomposition as in Table 2, but using our usual three age categories. Numbers in the first panel represent relative contributions to the growth-selection effect. Columns sum to one. The first row in the second panel shows the growth-selection effect within each broad occupation group during 1985–2010. The last four rows show $p^{ent,g}_{k,t}$ and $p^{lvr,g}_{k,t-1}$, averaged over the entire period.

Table C.3: Contributions to growth-selection by origin and destination activities

Type	Age	Source / Destination	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Entrants	25–34	Mgr-Prof-Tech		-0.004	0.002	0.001
		Sales-Office	0.023		0.007	0.008
		Prod-Op-Crafts	0.088	0.080		0.045
		Srvc-Care	0.007	0.014	0.009	
		Unemployment	0.067	0.052	0.090	0.056
		Out of the Labor Force	-0.007	-0.017	0.039	-0.019
		Sample Entrants	0.339	0.395	0.172	0.250
	35–54	Mgr-Prof-Tech		-0.046	-0.004	-0.003
		Sales-Office	-0.011		0.006	0.002
		Prod-Op-Crafts	0.046	0.032		0.023
		Srvc-Care	0.005	0.007	0.010	
		Unemployment	0.043	0.052	0.134	0.052
		Out of the Labor Force	-0.003	-0.008	0.053	-0.024
		Sample Entrants	0.038	0.081	0.061	0.097
Leavers	25–34	Mgr-Prof-Tech		0.027	0.001	0.004
		Sales-Office	0.047		0.004	0.014
		Prod-Op-Crafts	0.053	0.089		0.101
		Srvc-Care	0.009	0.014	0.006	
		Unemployment	0.035	0.042	0.100	0.057
		Out of the Labor Force	0.102	0.096	0.063	0.100
	35–54	Mgr-Prof-Tech		-0.078	-0.007	-0.002
		Sales-Office	-0.000		0.003	0.003
		Prod-Op-Crafts	0.046	0.054		0.050
		Srvc-Care	0.008	0.013	0.007	
		Unemployment	0.034	0.025	0.164	0.049
		Out of the Labor Force	0.094	0.117	0.089	0.126
		Sample Leavers	-0.063	-0.036	-0.009	0.009

Notes: Numbers represent relative contributions to the growth-selection effect over the 1985–2010 period. Columns sum to one. See the second panels of Table 2 or Table C.2 for the magnitude of growth-selection by occupation group.

Table C.4: Contributions to growth-selection by origin and destination activities, 3 age groups

Type	Age	Source / Destination	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Entrants	25–34	Mgr-Prof-Tech		-0.004	0.002	0.001
		Sales-Office	0.023		0.007	0.008
		Prod-Op-Crafts	0.088	0.080		0.045
		Srvc-Care	0.007	0.014	0.009	
		Unemployment	0.067	0.052	0.090	0.056
		Out of the Labor Force	-0.007	-0.017	0.039	-0.019
		Sample Entrants	0.339	0.395	0.172	0.250
	35–44	Mgr-Prof-Tech		-0.024	-0.003	-0.003
		Sales-Office	-0.005		0.004	0.002
		Prod-Op-Crafts	0.033	0.023		0.016
		Srvc-Care	0.003	0.004	0.006	
		Unemployment	0.030	0.032	0.085	0.026
		Out of the Labor Force	-0.002	-0.006	0.032	-0.015
		Sample Entrants	0.026	0.045	0.041	0.059
	45–54	Mgr-Prof-Tech		-0.023	-0.001	0.000
		Sales-Office	-0.006		0.001	-0.001
		Prod-Op-Crafts	0.014	0.009		0.007
		Srvc-Care	0.002	0.003	0.003	
		Unemployment	0.013	0.021	0.050	0.026
		Out of the Labor Force	-0.002	-0.002	0.022	-0.009
		Sample Entrants	0.012	0.036	0.020	0.037
Leavers	25–34	Mgr-Prof-Tech		0.027	0.001	0.004
		Sales-Office	0.047		0.004	0.014
		Prod-Op-Crafts	0.053	0.089		0.101
		Srvc-Care	0.009	0.014	0.006	
		Unemployment	0.035	0.042	0.100	0.057
		Out of the Labor Force	0.102	0.096	0.063	0.100
	35–44	Mgr-Prof-Tech		-0.042	-0.005	-0.001
		Sales-Office	0.007		0.002	0.003
		Prod-Op-Crafts	0.032	0.034		0.034
		Srvc-Care	0.004	0.006	0.005	
		Unemployment	0.025	0.015	0.095	0.025
		Out of the Labor Force	0.043	0.043	0.055	0.045
	45–54	Mgr-Prof-Tech		-0.037	-0.002	-0.001
		Sales-Office	-0.007		0.002	0.001
		Prod-Op-Crafts	0.015	0.019		0.016
		Srvc-Care	0.004	0.007	0.002	
		Unemployment	0.009	0.010	0.070	0.024
		Out of the Labor Force	0.051	0.074	0.034	0.081
		Sample Leavers	-0.063	-0.036	-0.009	0.009

Notes: Numbers represent relative contributions to the growth-selection effect over the 1985–2010 period. Columns sum to one. See the second panels of Table 2 or Table C.2 for the magnitude of growth-selection by occupation group.

Table C.5: Contributions to growth-selection by source of skills, detailed occupations

Source	Type	Age	Consultants, tax advisers	IT experts	Accountants, valuers	Type setters and printers	Machine operators	Assistant laborers	Cooks
Endowment at the most recent	Entrants	25–34	0.303	0.159	0.111	-0.003	0.034	0.198	0.348
entry into the occupation group		35–54	-0.320	-0.098	-0.188	-0.010	-0.050	0.179	0.080
	Leavers	25–34	0.281	0.134	0.099	0.052	0.070	0.193	0.296
		35–54	-0.369	-0.112	-0.112	0.082	0.079	0.184	0.099
Predicted **skill accumulation**	Entrants	25–34	0.467	0.371	0.317	0.287	0.108	0.034	0.049
since the most recent entry		35–54	0.280	0.174	0.367	0.178	0.129	0.026	0.016
	Leavers	25–34	0.079	0.094	0.073	0.059	0.027	0.014	0.017
		35–54	0.086	0.071	0.086	0.029	0.129	0.023	0.025
Deviation of skills from the	Entrants	25–34	0.082	0.066	0.054	0.111	0.118	0.037	0.033
prediction since the most recent		35–54	0.051	0.031	0.067	0.071	0.143	0.028	0.007
entry	Leavers	25–34	0.007	0.037	0.011	0.038	0.066	0.037	0.024
		35–54	0.053	0.074	0.114	0.105	0.147	0.045	0.005
Background									
Growth Selection	Total		-0.115	-0.202	0.104	0.130	0.093	-0.290	-0.091
Fractions	Entrants	25–34	0.633	0.669	0.489	0.635	0.467	0.574	0.636
		35–54	0.367	0.331	0.511	0.365	0.533	0.426	0.364
	Leavers	25–34	0.368	0.338	0.192	0.255	0.210	0.449	0.484
		35–54	0.632	0.662	0.808	0.745	0.790	0.551	0.516

Notes: This is the same decomposition as in Table 2 for selected detailed occupations. Numbers in the first panel represent relative contributions to the growth-selection effect. Columns sum to one. The first row in the second panel shows the growth-selection effect for each occupation during 1985–2010. The last four rows show $p_{k,t}^{ent,g}$ and $p_{k,t-1}^{lvr,g}$, averaged over the entire period. "Consultants, tax advisors" and "IT experts" are in Mgr-Prof-Tech; "accountants, valuers" in Sales-Office; "type setters and printers", "machine operators", and "assistant laborers" in Prod-Op-Crafts; and "cooks" in Srvc-Care occupation groups (see Table A.1).

Table C.6: Contributions to growth-selection by origin and destination activities, detailed occupations

Type	Age	Source / Destination	Consultants, tax advisers	IT experts	Accountants, valuers	Type setters and printers	Machine operators	Assistant laborers	Cooks
Entrants	25–34	Special printers, screeners				0.016			
		Roofers	0.001			0.009	0.005	0.001	
		Building laborer, building assistants	0.001			0.005	0.015	0.003	
		Electrical engineering and building technicians	0.001	0.008					
		Salespersons	0.014	0.005	0.004	0.002	0.001	0.001	0.003
		Motor vehicle drivers	0.003	0.003		0.002	0.025	0.001	
		Stowers, packers, stores/transport workers	0.001	0.004	0.002	0.002	0.011	0.007	0.003
		Consultants, tax advisers		0.001	0.024				
		Office specialists	0.045	0.027	0.109	0.002		0.001	
		Bar keepers, waiters, stewards	0.003		0.003	0.001		0.001	0.014
		Others attending on guests		0.001				0.001	0.009
		Unemployment	0.059	0.085	0.050	0.059	0.035	0.088	0.040
		Out of the Labor Force	0.068	0.032	0.036	0.025	0.002	0.009	-0.022
		Sample Entrants	0.594	0.350	0.217	0.219	0.094	0.122	0.343
	35–54	Special printers, screeners				0.034	0.001		
		Metal workers (no further specification)		0.001			0.002	0.004	
		Building laborer, building assistants				0.001	0.018	0.004	0.003
		Electrical engineers	-0.009	-0.006	-0.003				
		Survey engineers, other engineers	-0.019	-0.002	-0.005				
		Salespersons	0.007	0.003		0.001	0.002	0.001	0.005
		Motor vehicle drivers	0.002	0.001	0.004	0.002	0.019	0.004	0.002
		Stowers, packers, stores/transport workers	0.003	0.004	0.001	0.001	0.008	0.005	
		Entrepreneurs, senior managers	-0.026	-0.005	-0.021	-0.004			0.001
		IT experts	-0.028		-0.009	0.003			
		Office specialists	-0.003	0.009	0.062	0.001	-0.001		
		Artistic and performance occupations				-0.009			
		Household and buildings cleaners						0.002	0.011
		Unemployment	0.051	0.055	0.093	0.083	0.071	0.117	0.019
		Out of the Labor Force	0.010	0.007	0.029	0.032	0.012	0.010	-0.029
		Sample Entrants	0.048	0.032	0.082	0.066	0.030	0.064	0.077
Leavers	25–34	Paper product and cellulose makers				0.006		0.001	0.001
		Special printers, screeners				0.007			0.001
		Assistant laborers		0.001		0.002	0.008		0.005
		Electrical engineering and building technicians		0.011	0.001		0.001	0.001	
		Wholesale and retail buyers	0.003	0.004	0.006	0.001			
		Tourism specialists, cashiers, ticket inspectors	0.002	0.001		0.005		0.001	0.001
		Motor vehicle drivers	0.002	0.002	-0.001		0.020	0.007	0.008
		Warehouse managers, warehousemen	0.002	0.002	0.003		0.003	0.006	0.015
		Stowers, packers, stores/transport workers	0.005	0.010			0.004	0.018	0.014
		Accountants, valuers	0.033	0.004					
		IT experts	0.027		0.009	0.004			
		Office specialists	0.072	0.033	0.074	0.004	0.001	0.002	0.001
		Bar keepers, waiters, stewards	0.003		-0.001			0.001	0.022
		Others attending on guests	0.003						0.014
		Unemployment	0.055	0.037	0.029	0.051	0.049	0.054	0.057
		Out of the Labor Force	0.125	0.074	0.032	0.040	0.026	0.086	0.090
	35–54	Bricklayers, concrete workers					0.004	0.002	-0.007
		Building laborer, building assistants	0.001				0.009	0.004	0.003
		Assistant laborers				0.009	0.001		0.002
		Electrical engineers	-0.007	-0.011	-0.004				
		Other technicians	-0.002	0.002	0.001	-0.007	-0.003		
		Bank and building society specialists	-0.014		-0.003				
		Motor vehicle drivers	0.001	0.004	0.006	0.001	0.021	0.007	0.003
		Stowers, packers, stores/transport workers	0.001	0.006	0.001		0.007	0.013	0.003
		Entrepreneurs, senior managers	-0.090	-0.023	-0.045	-0.003	-0.002		
		IT experts	-0.038		-0.005	-0.002			
		Office specialists	-0.010	0.008	0.024	0.007	0.001	0.001	0.003
		Others attending on guests							0.010
		Household and buildings cleaners					0.001	0.002	0.009
		Unemployment	0.035	0.031	0.063	0.109	0.121	0.069	0.018
		Out of the Labor Force	0.009	0.055	0.135	0.100	0.146	0.093	0.065
		Sample Leavers	-0.099	-0.037	-0.072	-0.025	0.027	0.013	-0.007

Notes: Numbers represent relative contributions to the growth-selection effect over the 1985–2010 period. See the second panel of Table C.5 for the magnitude of growth-selection by occupation. The origin/destination occupations are chosen as the five main contributors to growth selection within a type-age-occupation category. Numbers that would be rounded to zero (i.e., smaller than 0.0005) are not shown. The sign and size of growth-selection for the column occupations are reported in Table C.5.

D Robustness of Estimated Price and Skill Changes

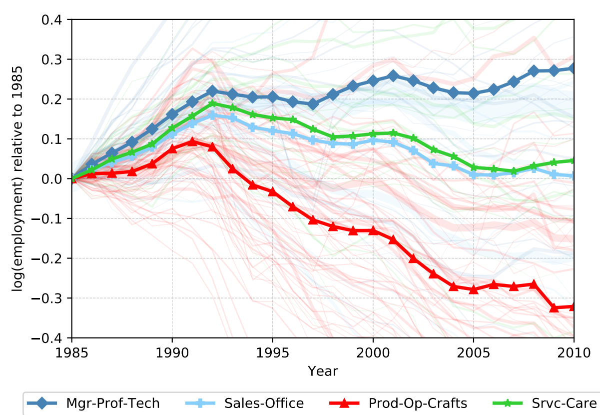
Section 4 of the main text has estimated the average skill accumulation and changes in skill prices for detailed occupations as well as broader groups. We found that skill prices in fact increased with employment growth in Germany during 1985–2010, contrary to changes in average wages across occupations, and that growth-selection accounts for much of the systematic skill changes implied by the estimation. This section shows that these results are robust to various alternative sample definitions and estimation specifications.

D.1 Separate "Wage" and "Employment" Samples as in Katz and Murphy (1992)

We re-draw our key graphs with occupational growth on the x-axes among a comprehensive "employment sample". In that sample, we include women and foreigners while expanding the considered age range to 20–60. Consistent with Katz and Murphy (1992), we keep prime age West German males for the wages, skill prices, and skills on the y-axes, since these are better measured in a high-attachment "wage sample".

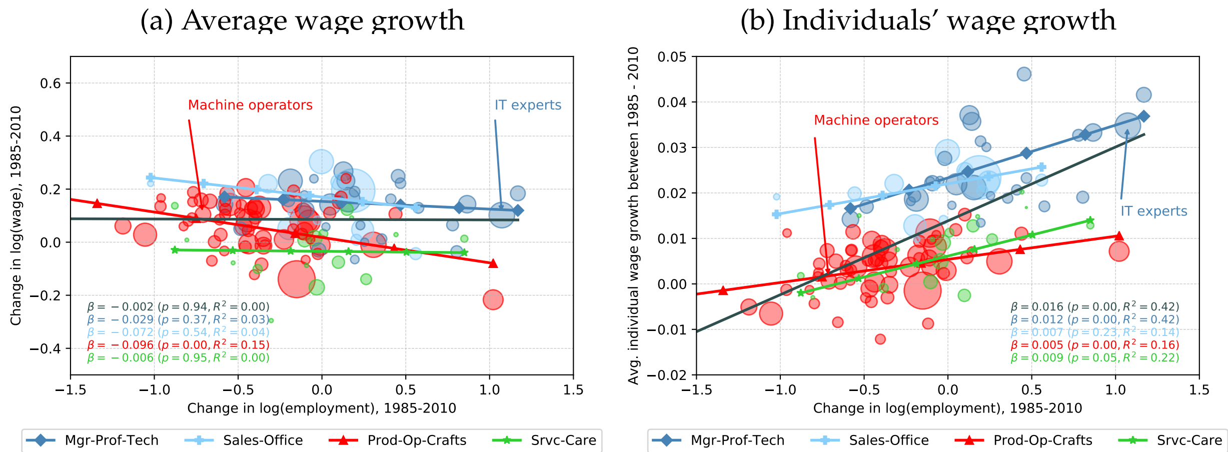
Employment growth in Figure D.1 is more extreme in Mgr-Prof-Tech (growing faster when especially women are included) and Prod-Op-Crafts (shrinking faster). Employment in Sales-Office and Srvc-Care is essentially unchanged over the whole 1985–2010 period. Overall, our stylized facts (e.g., employment growth and wage growth are uncorrelated in Figure D.2a) and estimation results (employment growth and price growth are positively correlated in Figure D.4a) turn out qualitatively very similar to the main text. In Figure D.5c and D.5d growth-selection is not forced through origin anymore, although the aggregate is close to it.

Figure D.1: Occupations' employment (comprehensive sample)



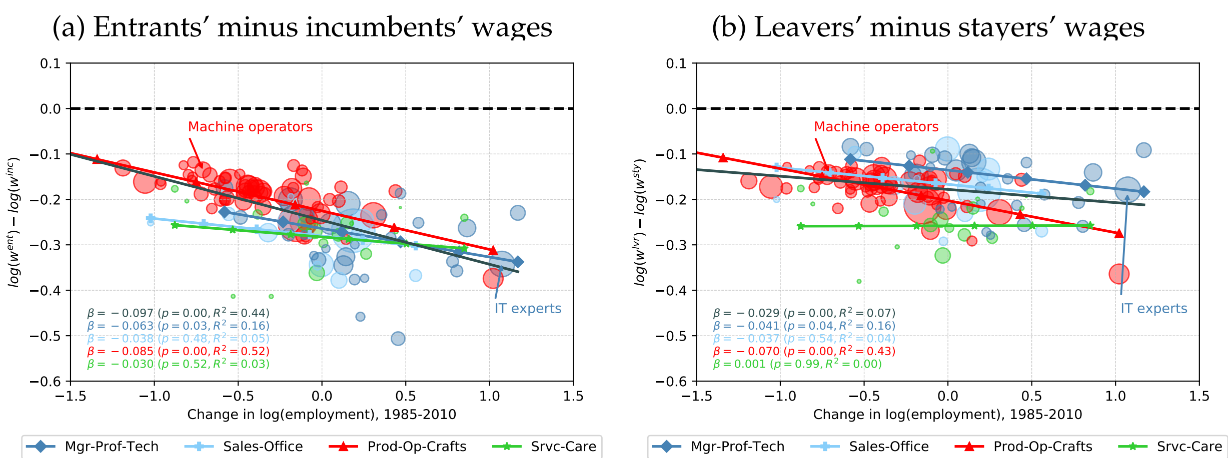
Notes: The vertical axis shows the log change in the number of employed workers within an occupation over time. Shaded lines in the background represent the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1.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

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



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

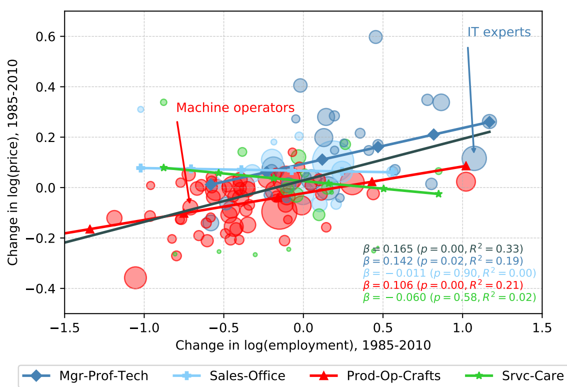
Figure D.3: Selection into and out of occupations



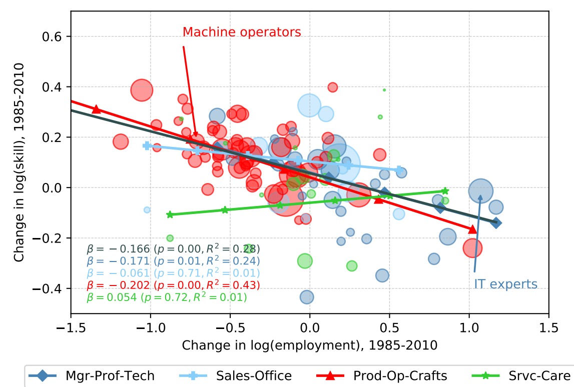
Notes: The vertical axis in Panel a shows the average wage of an entrant to an occupation relative to the average wage of incumbents. The average wage is taken across years 1985 until 2010. The vertical axis in Panel b shows the average wage of a worker leaving an occupation next period relative to the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

Figure D.4: Correlation of changes in employment, skill prices, and skills

(a) Skill prices

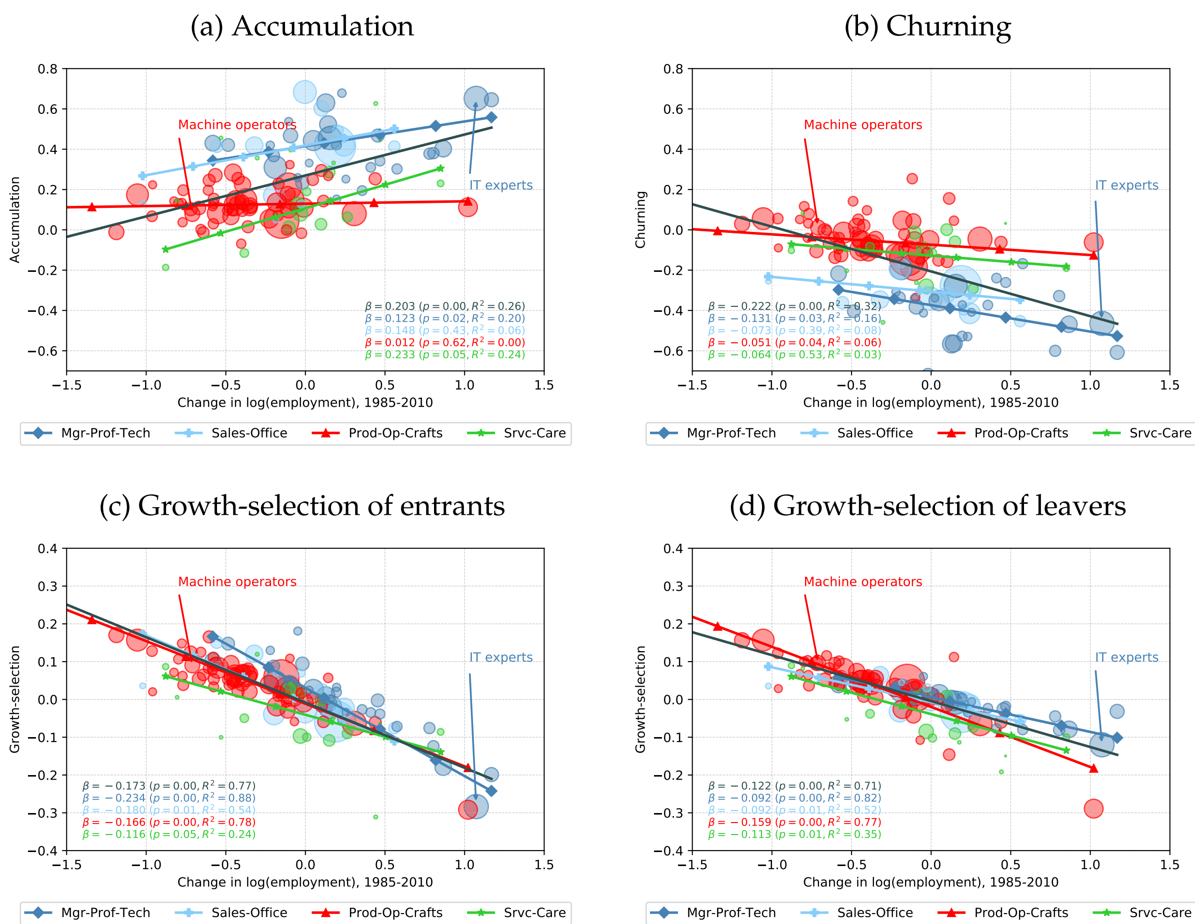


(b) Skills



Notes: The vertical axis in Panel a shows the change in skill prices between 1985 and 2010 estimated as detailed in Section 3.2. The vertical axis in Panel b depicts the change in skills between 1985 and 2010 estimated as the residual between price and wage changes as shown in Equation (8). The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.5: Employment growth vs. the components of skill changes



Notes: Results correspond to sample averages following Equation (9). The horizontal axis in both panels shows the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

D.2 Alternative Samples

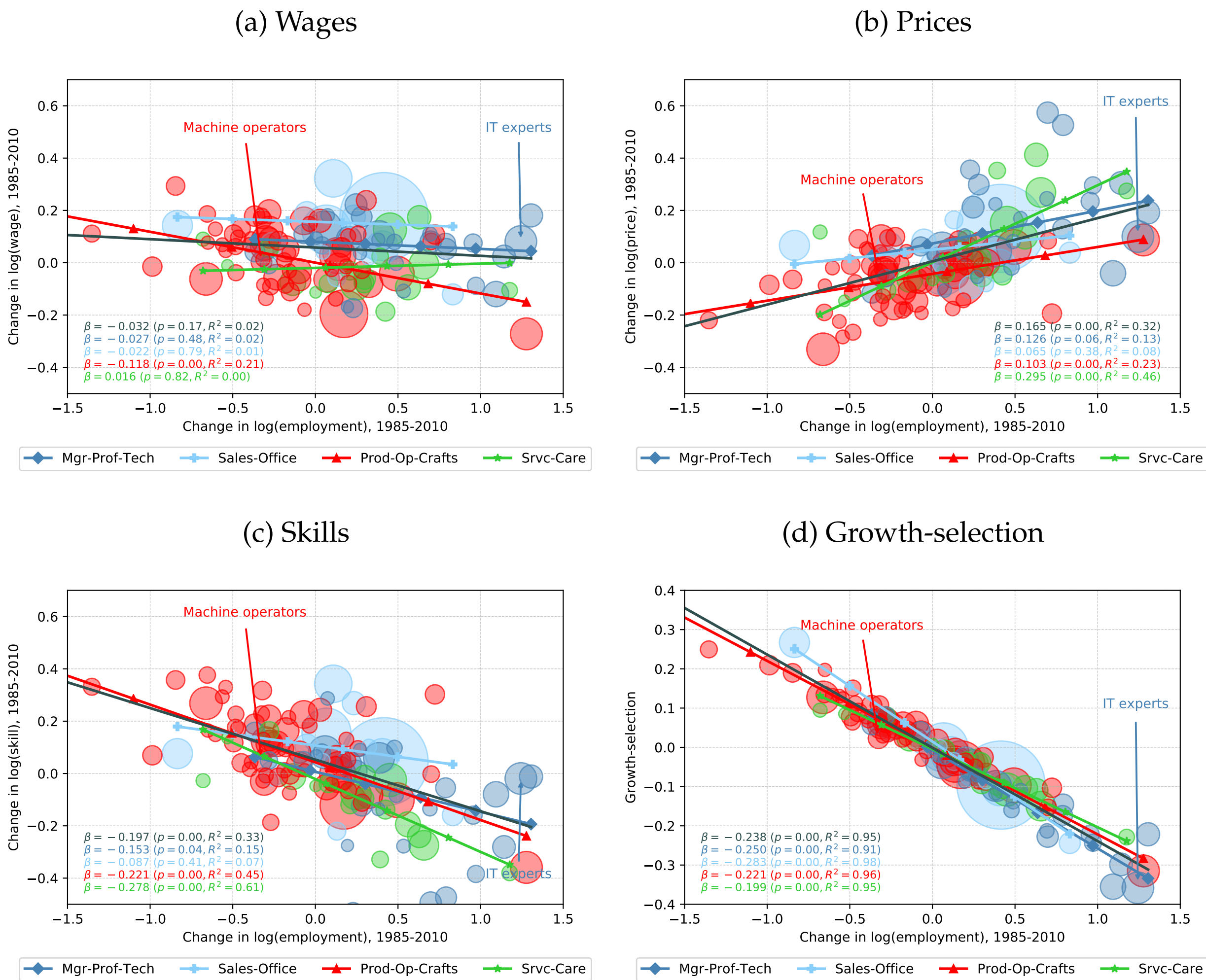
We have restricted our main sample to West German men as these can be defined consistently over the 1975–2010 period and many potentially confounding factors that may have affected women or foreigners, such as higher labor force participation, declining workplace discrimination (e.g., Hsieh et al., 2019), and rapidly rising educational attainment, do not apply. Nonetheless, the entry of women and foreigners as well as the reunification with the East constituted major supply shifts affecting the German labor market during our sample period. If women or foreigners were more inclined to work in Srvc-Care, for example, rising employment and falling wages in these occupations may be due to changes in labor supply. Also, if women or foreigners tend to earn less in certain occupations, estimated skill prices may be confounded by the closing of such gender or racial wage gaps over time. We therefore examine whether general equilibrium and composition effects due to supply shifts are important by checking if our estimates differ when we include these groups in our sample.

Figure D.6 shows that skill prices hardly change when we include everyone, that is, women (increases sample by circa 69%), foreigners (6%), and individuals working in East Germany (15%), in the estimation. The implied skill changes and the growth-selection effect are somewhat steeper than in our main sample but qualitatively the same. Still more notable, when we estimate our model for prime aged West German women only, the relationship between occupations' skill price and employment growth is even stronger than for prime age men (i.e., 0.19 versus 0.15 slope of the regression line in Figure D.7) and skill prices similarly tend to polarize (i.e., rise for the Mgr-Prof-Tech, Sales-Office, and Srvc-Care occupation groups). The same is true when dropping all workers whose nationality changes over the life cycle (Figure D.8).

It is interesting to see that these results are similar despite a substantially different employment structure, with many more Sales-Office and Srvc-Care occupations among women than among men (becoming visible in the different bubble sizes). The results indicate that occupational demand shifts have largely driven the employment and skill price changes also for women, foreigners, and East Germans; apparently dominating other forces that may have worked on these demographic groups' changing labor market outcomes.

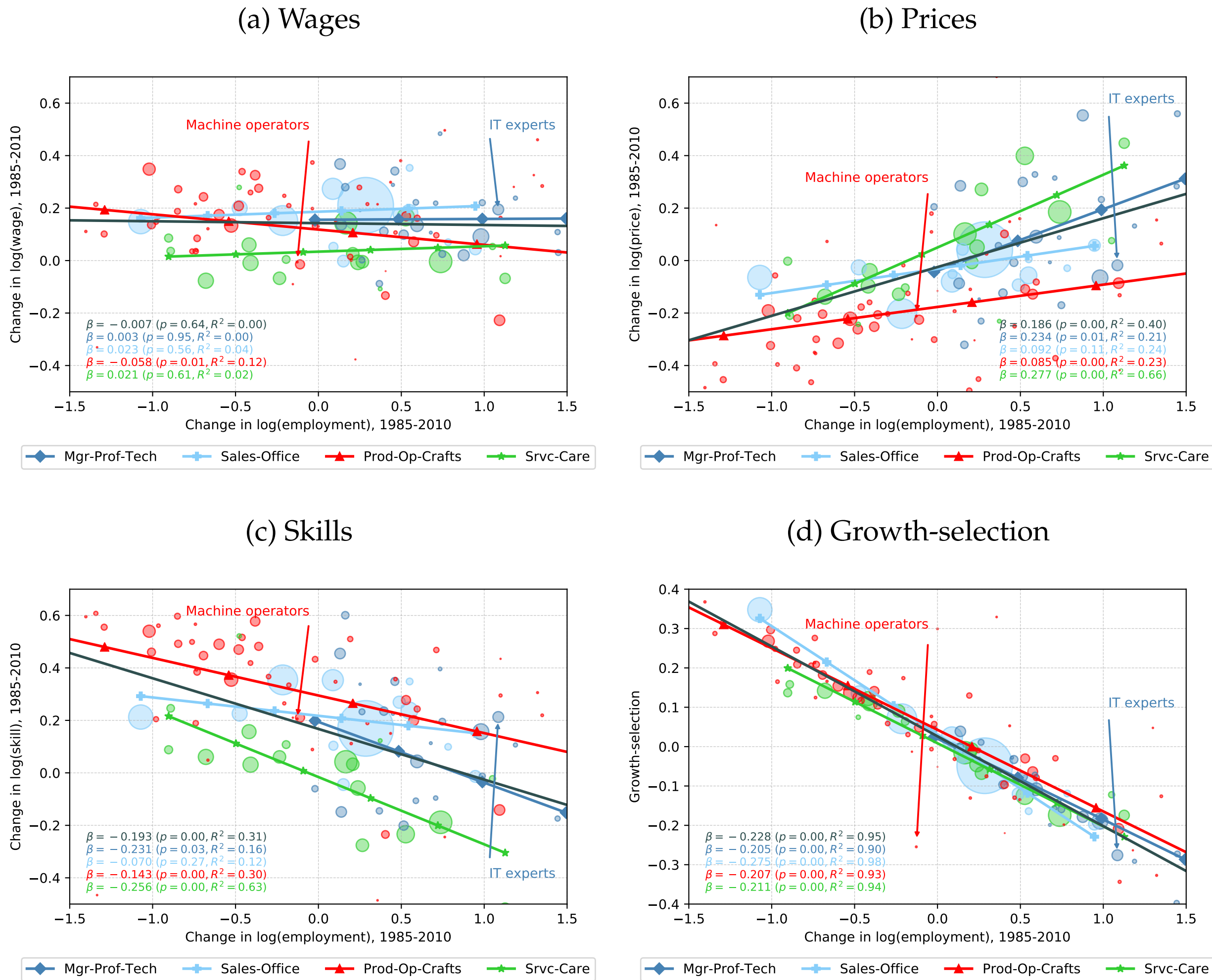
Finally, we widen the age range to 20–60 year old males. The results, depicted in Figure D.9, are largely similar to our main prime age sample, with somewhat steeper slopes but also stronger growth-selection. The latter makes sense if labor market entrants in their early twenties were even less skilled compared to incumbents and lower-skilled workers were more likely to retire early.

Figure D.6: Including East Germans, foreigners, and women



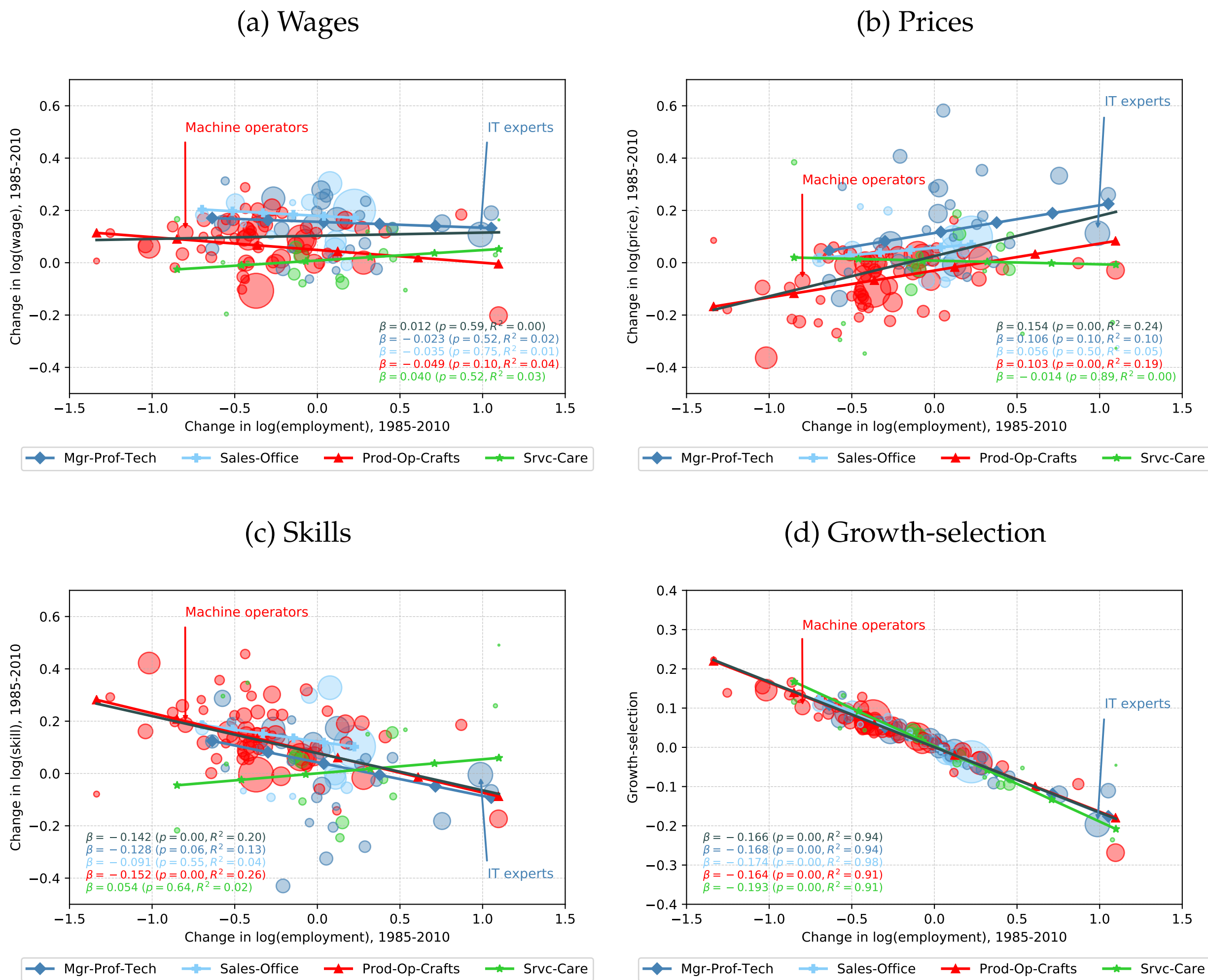
Notes: The sample additionally includes East Germans, foreigners and women. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.7: Women only



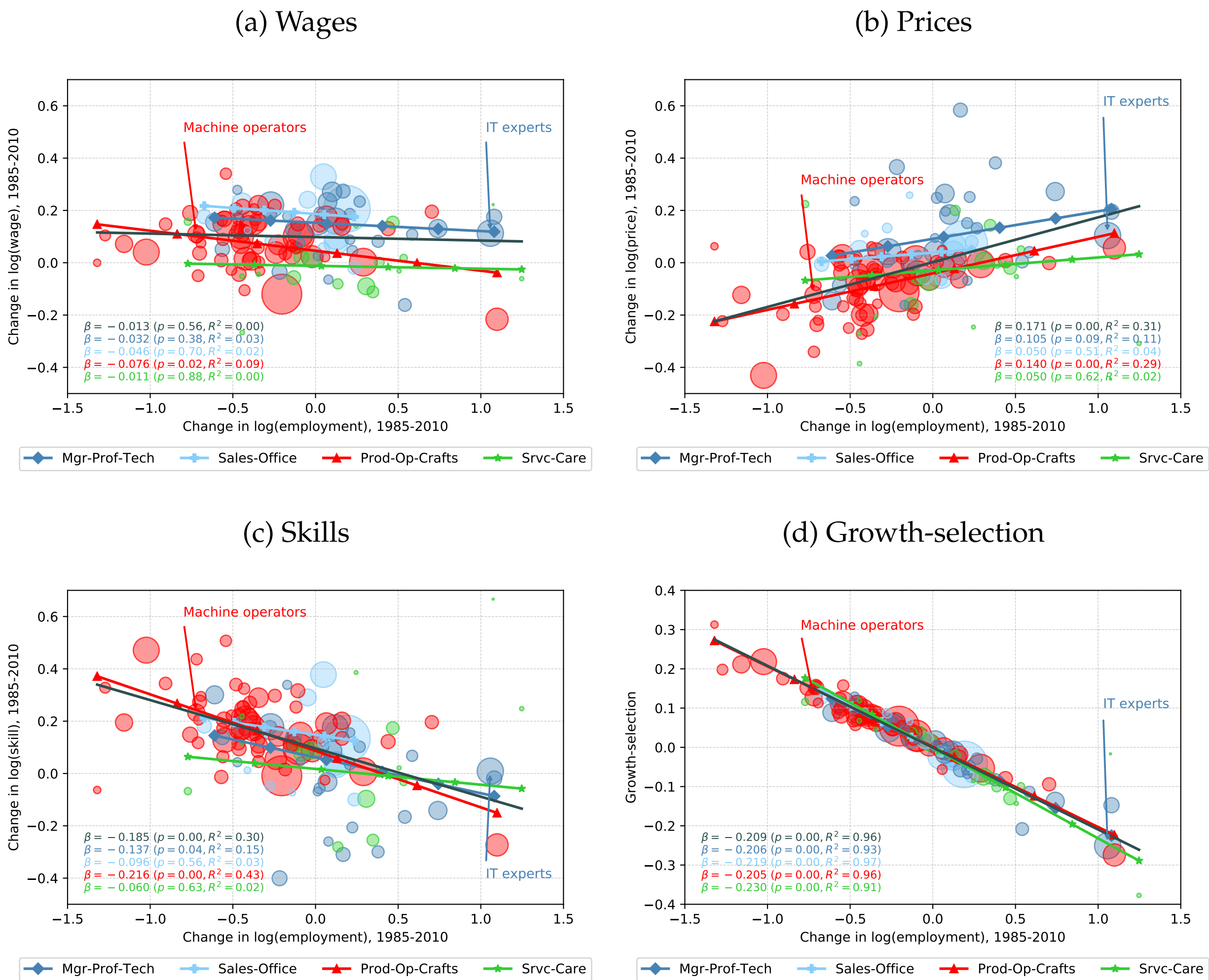
Notes: The sample is restricted to (full-time working) women. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.8: Excluding anybody ever coded as a foreigner



Notes: The sample is the same as the baseline sample except that we also drop workers which are reported to be foreigners at some point in time. This includes, for instance, workers acquiring the German nationality at some later point in the life cycle. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.9: All ages, 20–60 year olds



Notes: The sample is restricted to 20–60 year old men. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

D.3 Unemployment and Dropping Out of the Labor Force as Choices

A key robustness check is to allow for endogenous unemployment and exit from the labor force. In the main estimation we have assumed that coming into and exiting the sample is exogenous. This is obvious for individuals who reach age 25 or 54 (the borders of our sample age range) but it might not be an innocuous assumption during the career. In particular, workers may *choose to* become unemployed or exit the labor force if they obtain a sufficiently bad idiosyncratic skill shock or vice versa for a sufficiently good shock, and if the (time-limited) benefits or other non-labor income they obtain are sufficiently high. Our model would then be misspecified with unclear effects for the consistency of our estimates.

In Figure D.10, we therefore assume that becoming unemployed or leaving the labor force temporarily is fully endogenous.[15] We do this by imputing workers' wages and their occupation choices if they are unemployed or out of the labor force for any number of years between two spells of employment. We impute those by comparing pre and post non-employment wages and assigning workers the lower of those two wages adjusted for inflation. That is, we assume that workers could well have worked in the lower paying occupation but chose to become unemployed or exit the labor force for some period of time instead. On this sample, which is about 10% larger in size (further details in Section A.1.4), we then repeat the estimation.

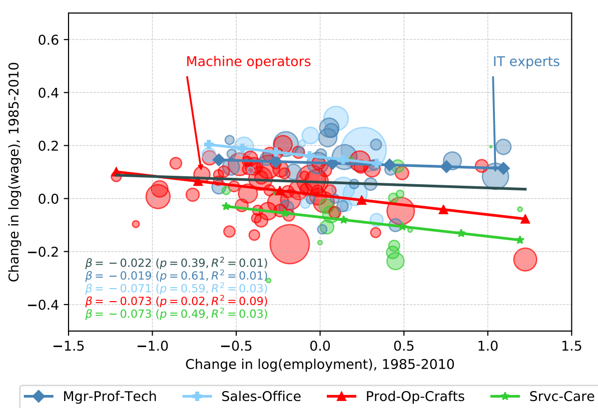
As mentioned in the main text already, the off-diagonal accumulation parameters when workers switch with intermittent non-employment spells, especially into Prod-Op-Crafts and Srvc-Care occupations, tend to be lower in Table D.1 than in Table C.1 above. The correlation between wage and employment growth is approximately zero in Figure D.10, but it is strongly positive between price and employment growth. A slightly flatter slope is induced by some fast growing occupations with many entrants from unemployment or out of the labor force spells whose estimated price growth diminishes when filling up those non-employment spells.[16] Finally, the implied skill changes are again negative and quite closely related to growth-selection.

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

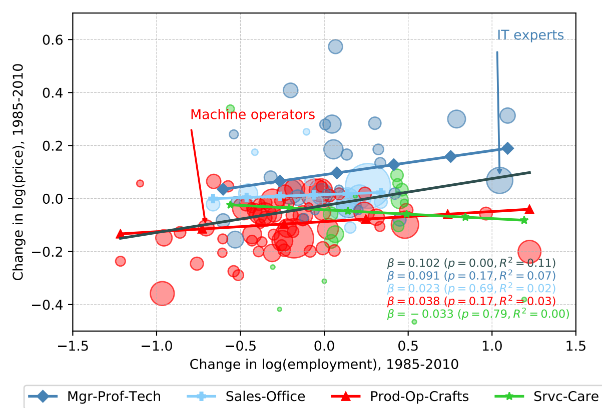
[16]One example are the "assistant laborers" also discussed in the main text. They constitute a fairly low earning group with increasing turnover during the sample period. Instead of moving into that occupation, many workers might prefer to become unemployed or leave the labor force. Hence, we (increasingly) fill non-employment spells of later entrants to the assistants occupation up with low wages. This translates into lower price growth compared to the baseline sample. However, in total, these effects are not strong enough to substantially influence our estimates.

Figure D.10: Unemployment and leaving the labor force as a choice, i.e., filled non-employment spells

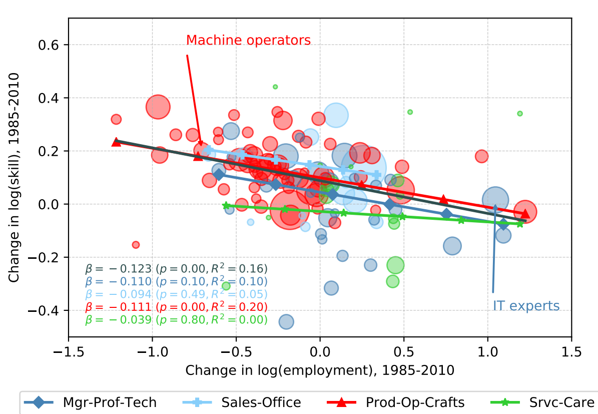
(a) Wages



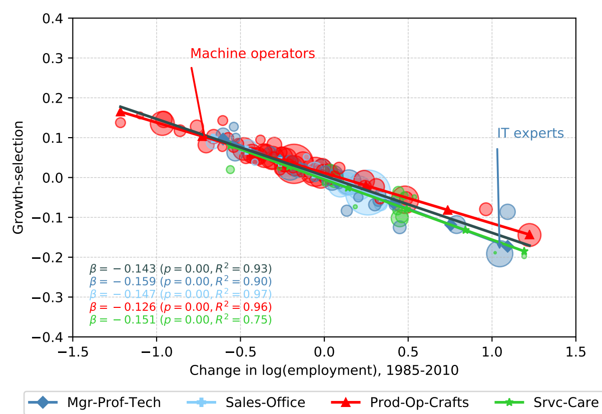
(b) Prices



(c) Skills



(d) Growth-selection



Notes: Unemployment and out of labor force spells are imputed by comparing the (real) wage after a non-employment spell with the wage before the non-employment spell. We then fill up the wage while in non-employment as the lower of those two wages adjusted for inflation and set the occupation within this time to the occupation that corresponds to that lower wage. See Appendix A.1.4 for the details. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Table D.1: Estimated skill accumulation coefficients (occupation groups), filled non-employment spells

			Age group		
Previous sector	Current sector		[25, 34]	[35, 44]	[45, 54]
Mgr-Prof-Tech	Mgr-Prof-Tech	γ	0.045	0.015	0.002
		σ_γ	0.000	0.000	0.000
	Sales-Office	γ	0.093	-0.042	-0.135
		σ_γ	0.004	0.004	0.005
	Prod-Op-Crafts	γ	-0.043	-0.167	-0.210
		σ_γ	0.005	0.005	0.006
	Srvc-Care	γ	-0.238	-0.398	-0.401
		σ_γ	0.011	0.011	0.015
Sales-Office	Mgr-Prof-Tech	γ	0.246	0.062	0.001
		σ_γ	0.003	0.004	0.005
	Sales-Office	γ	0.041	0.014	0.000
		σ_γ	0.000	0.000	0.000
	Prod-Op-Crafts	γ	0.030	-0.050	-0.156
		σ_γ	0.004	0.005	0.006
	Srvc-Care	γ	-0.225	-0.331	-0.279
		σ_γ	0.008	0.010	0.013
Prod-Op-Crafts	Mgr-Prof-Tech	γ	0.250	0.161	0.066
		σ_γ	0.003	0.004	0.005
	Sales-Office	γ	0.047	0.067	-0.028
		σ_γ	0.003	0.004	0.006
	Prod-Op-Crafts	γ	0.016	0.007	-0.008
		σ_γ	0.000	0.000	0.000
	Srvc-Care	γ	-0.237	-0.185	-0.144
		σ_γ	0.004	0.004	0.005
Srvc-Care	Mgr-Prof-Tech	γ	0.405	0.290	0.171
		σ_γ	0.009	0.011	0.016
	Sales-Office	γ	0.211	0.162	0.049
		σ_γ	0.008	0.010	0.015
	Prod-Op-Crafts	γ	0.259	0.186	0.106
		σ_γ	0.004	0.005	0.007
	Srvc-Care	γ	0.013	0.004	-0.010
		σ_γ	0.001	0.001	0.001

Notes: The table shows the estimated $\hat{\gamma}_{k',k,a}$ for age groups a. k' is last period's occupation. k is the current occupation. Unemployment and out of labor force spells are imputed by comparing the (real) wage after a non-employment spell with the wage before the non-employment spell. We then fill up the wage while in non-employment as the lower of those two wages adjusted for inflation and set the occupation within this time to the occupation that corresponds to that lower wage. See Appendix A.1.4 for the details.

Table D.2: Contributions to growth-selection by source of skills, filled non-employment spells

Source	Type	Age	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Endowment at the most recent entry into the occupation group	Entrants	25–34	0.251	0.265	0.128	0.363
		35–54	-0.046	-0.057	0.063	0.065
	Leavers	25–34	0.168	0.171	0.094	0.227
		35–54	-0.162	-0.208	0.072	-0.028
Predicted **skill accumulation** since the most recent entry	Entrants	25–34	0.271	0.330	0.187	0.048
		35–54	0.106	0.108	0.068	0.022
	Leavers	25–34	0.036	0.062	0.036	0.001
		35–54	0.126	0.172	0.023	0.070
Deviation of skills from the prediction since the most recent entry	Entrants	25–34	0.068	0.035	0.134	0.034
		35–54	0.024	0.004	0.048	0.010
	Leavers	25–34	0.055	0.048	0.047	0.060
		35–54	0.104	0.072	0.100	0.128
Background						
Growth Selection	Total		-0.033	-0.020	0.047	-0.041
Fractions	Entrants	25–34	0.667	0.683	0.783	0.622
		35–54	0.333	0.317	0.217	0.378
	Leavers	25–34	0.225	0.293	0.266	0.372
		35–54	0.775	0.707	0.734	0.628

Notes: This is the same decomposition as in Table 2, but for the sample with filled-up non-employment spells. Numbers in the first panel represent relative contributions to the growth-selection effect. Columns sum to one. The first row in the second panel shows the growth-selection effect within each broad occupation group during 1985–2010. The last four rows show $p_{k,t}^{ent,g}$ and $p_{k,t-1}^{lvr,g}$, averaged over the entire period.

Table D.3: Contributions to growth-selection by origin and destination activities, filled non-employment spells

Type	Age	Source / Destination	Mgr-Prof-Tech	Sales-Office	Prod-Op-Crafts	Srvc-Care
Entrants	25–34	Mgr-Prof-Tech		-0.004	0.006	0.003
		Sales-Office	0.032		0.024	0.015
		Prod-Op-Crafts	0.164	0.142		0.089
		Srvc-Care	0.013	0.022	0.032	
		Out of the Labor Force	0.032	0.014	0.048	-0.000
		Sample Entrants	0.350	0.456	0.339	0.339
	35–54	Mgr-Prof-Tech		-0.053	-0.001	0.000
		Sales-Office	-0.014		0.026	0.002
		Prod-Op-Crafts	0.046	0.046		0.035
		Srvc-Care	0.008	0.008	0.039	
		Out of the Labor Force	0.006	0.004	0.030	0.001
		Sample Entrants	0.037	0.050	0.085	0.060
Leavers	25–34	Mgr-Prof-Tech		0.060	0.023	0.030
		Sales-Office	0.058		0.029	0.028
		Prod-Op-Crafts	0.075	0.124		0.140
		Srvc-Care	0.015	0.028	0.026	
		Out of the Labor Force	0.111	0.069	0.099	0.090
	35–54	Mgr-Prof-Tech		-0.091	-0.012	-0.003
		Sales-Office	0.002		0.011	0.001
		Prod-Op-Crafts	0.050	0.066		0.052
		Srvc-Care	0.012	0.017	0.029	
		Out of the Labor Force	0.094	0.119	0.219	0.158
		Sample Leavers	-0.091	-0.075	-0.052	-0.038

Notes: Numbers represent relative contributions to the growth-selection effect over the 1985–2010 period. Columns sum to one. See the second panel of Table D.2 for the magnitude of growth-selection by occupation group. The rows labeled "Out of the labor force" refer to individuals who enter the sample after age 25 or who leave and do not return to the sample.

D.4 Alternative Estimation Specifications

This section presents the results from various extensions to our baseline method. Except for the flat-spot identification approach, all these extensions are applied to the main sample of prime age, West German, full-time working men.

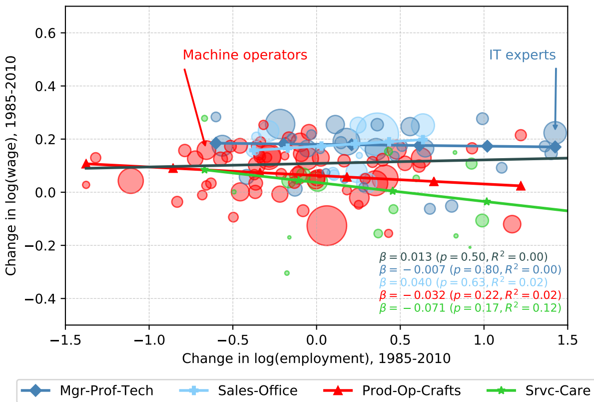
Noting that skill accumulation is rather flat for 45–54 year olds (e.g., Figure 5b), we apply Heckman et al. (1998)'s flat spot identification strategy to this age group by setting skill accumulation to zero in all occupations. We see in Panel D.11a that wage growth is again uncorrelated with employment growth in this older subsample whereas in Panel D.11b skill price growth once more increases with occupations' size growth. This positive relationship is even stronger than in the full sample (regression slope of 0.18 compared to 0.15). Growth-selection does not fully account for the systematic skill changes anymore but still for more than half (also, the assumption of zero skill changes might not be strictly correct). These results indicate that also in samples where skill accumulation is arguably more or less constant, and when dynamic considerations should not be a large concern, we get similar results.

In the main estimation, skill accumulation varies by combination of current and last year's occupation as well as by age in order to account for the differential life-cycle wage growth in these dimensions. In Figure D.13, we also allow for the fact that skill accumulation may additionally vary by the worker's education level on top of detailed occupation and age. Practically, considering skill accumulation Equation (5), we add dummies for high (university or college degree), medium (apprenticeship or Abitur), and low (without postsecondary) education level to the worker characteristics and the according coefficients to the Γ parameter matrix. Skill accumulation is faster for highly educated workers in almost every occupation. Nonetheless, the elasticity of skill price changes with respect to employment growth is only slightly lower than the baseline elasticity, and the other results are also similar.

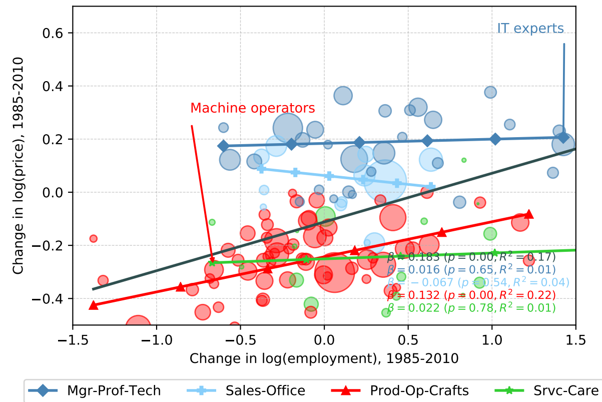
Alternatively, in Figure D.12 we control for occupation-specific skill changes only, without interacting by age. The price and skill change estimates are again similar (i.e., our main results unaffected). But, by construction, skill accumulation in each occupation is completely linear over the career and thus seems too stylized. In contrast, Figure D.14 includes control variables for dummies per year of potential experience flexibly interacted with education (no postsecondary, Abitur or apprenticeship, and university degree) to our estimation for the four broad occupation groups. In Figure D.14b the skill accumulation profiles including these potexp $\times$ education dummies are not piecewise linear anymore, but indeed concave over the life-cycle as one would expect. Figure D.14a however shows that the estimated changes in skill prices, which are the focus of our analysis, hardly change. Prices in 2010 for Prod-Op-Crafts and Srvc-Care are very similar to Figure 5a in the main text while prices for Mgr-Prof-Tech and Sales-Office are only slightly lower.

Figure D.11: Flat spot identification using workers aged 45–54 years

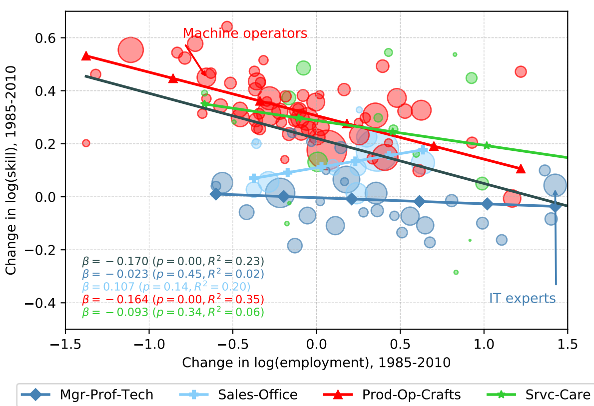
(a) Wages



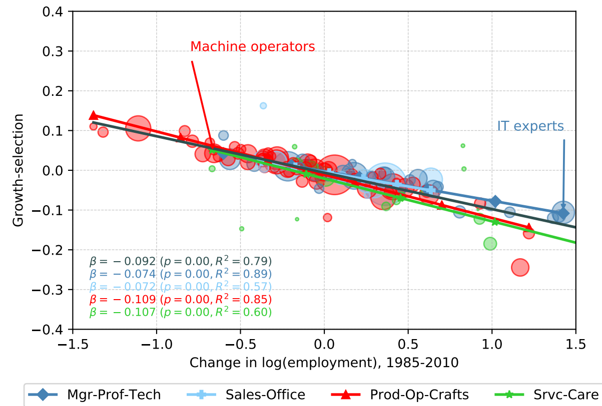
(b) Prices



(c) Skills

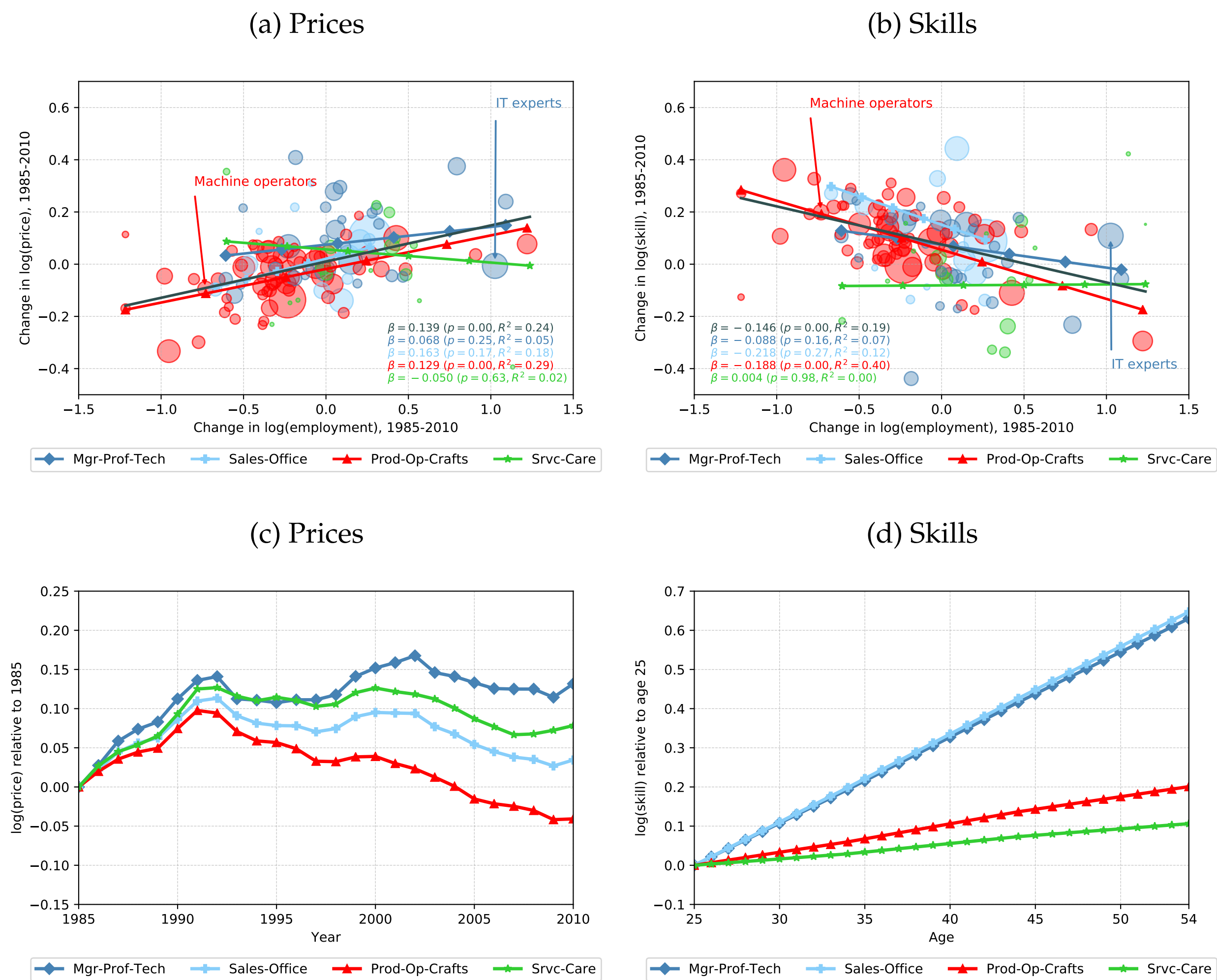


(d) Growth-selection



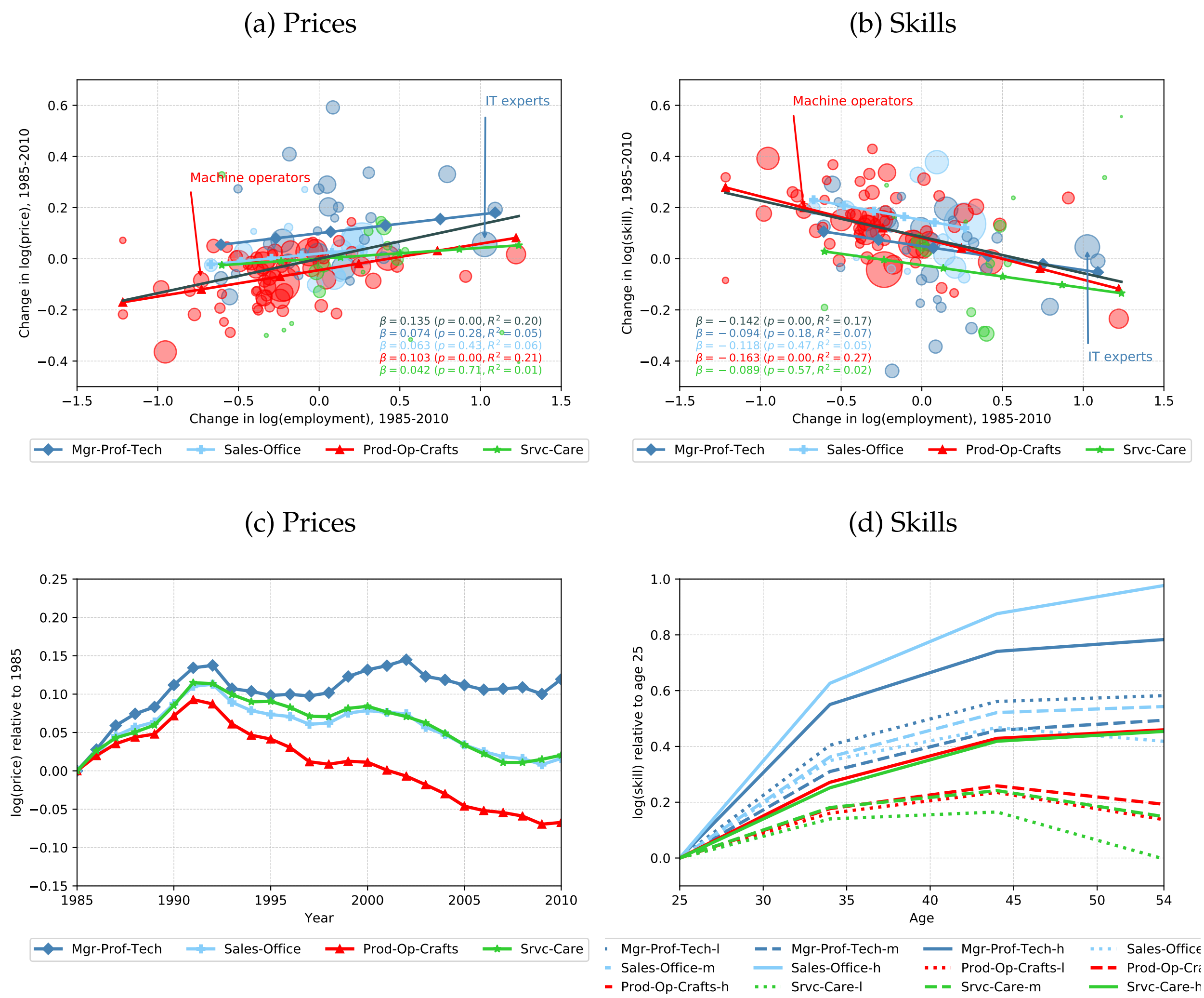
Notes: The sample is restricted to 45–54 year old men. Skill accumulation is set to zero across occupations. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.12: Occupation-specific skill accumulation only



Notes: The speed of skill accumulation described by Equation (5) does not depend on age. The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

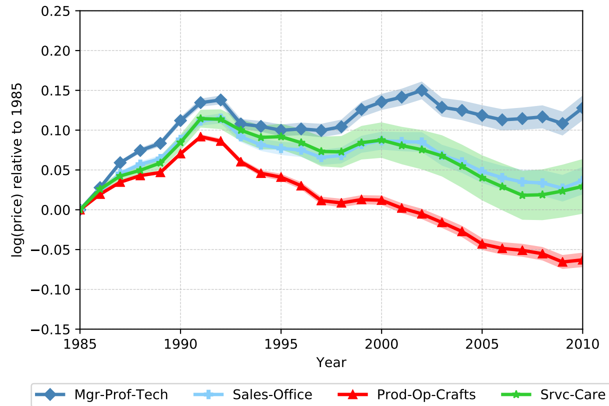
Figure D.13: Education-age-occupation-specific skill accumulation



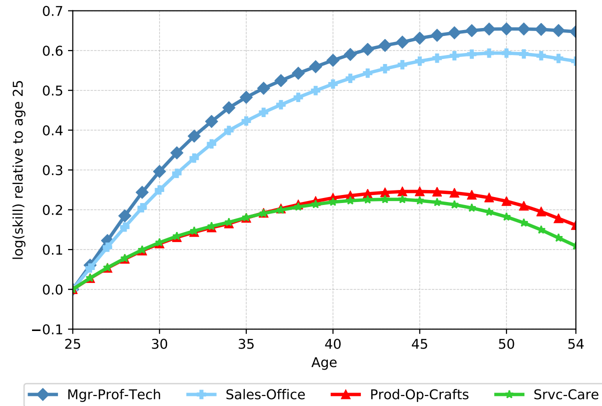
Notes: The speed of skill accumulation described by Equation (5) is allowed to vary with worker's education by including dummies for three education levels low (missing or without any postsecondary education), medium (apprenticeship training or high school diploma), and high (university degree)). The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.14: Skill accumulation specific to age × occupation + potential experience

(a) Prices



(b) Skills



Notes: The speed of skill accumulation described by Equation (5) is allowed to vary with worker's education by including dummies for three education levels (low (missing or without any postsecondary education), medium (apprenticeship training or high school diploma), and high (university degree)). The horizontal axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

D.5 Task Measures and Changes in Occupations' Employment, Wages, Prices, and Skills

Our data on tasks that workers typically perform on the job comes from the Qualification and Career Surveys (QCS), which are conducted by the Federal Institute for Vocational Education and Training (BIBB) and have previously been used to study task intensities (see for instance Spitz-Oener (2006), Antonczyk et al. (2009), Black and Spitz-Oener (2010), or Gathmann and Schönberg (2010)). The QCS are representative cross-sectional surveys with roughly 20,000–35,000 respondents in each wave. There are six waves available, which were conducted in 1979, 1985/86, 1991/92, 1998/99, 2006 and 2012. The surveys contain detailed questions about tasks that are required in the workers' occupations, such as how often they repair objects or how often they have to persuade co-workers. We classify each question as representing either analytical, interactive, routine, or manual tasks and assign a value of 0, $\frac{1}{3}$ or 1, depending on whether the answer is 'never', 'sometimes', or 'frequently' (or 0/1 for yes/no questions). Since the questions are not always comparable across waves, we pool all waves to compute task intensities by averaging over all responses. Note that the intensities are constructed in a way so that the four dimensions do not sum to 1, which follows the approach in Spitz-Oener (2006). There are two types of variation in responses that lead to variation in absolute task intensities across occupations. First, at the "extensive margin" fewer or more workers can reply that they engage in a task that is asked for in a specific question at all. As an example, consider the simple case with two questions about analytical tasks and individuals in one occupation doing both tasks and individuals in the other occupation only one. Second, at the "intensive margin", individuals in the occupation could more or less often reply that they engage 'sometimes' in a task, as opposed to 'frequently'.

Figure D.15 shows that occupations intensive in analytical (Mgr-Prof-Tech) and interactive (Mgr-Prof-Tech and Sales-Office) tasks indeed grew quite strongly, whereas employment in routine-intensive (Prod-Op-Crafts) occupations declined.

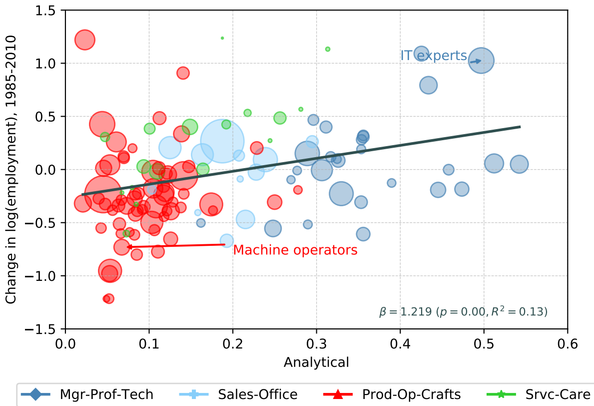
High analytical and interactive task content predict rising wages (Figure D.16), but the relation with skill prices is even steeper (D.17). Conversely, implied skills deteriorate in analytical and interactive task content (Figure D.18). The correlation between routine task intensity and changing average wages is zero; this is composed of falling prices and rising skills. All this is consistent with the impact of RBTC on these occupations and with our finding that skill price changes are counteracted by selection effects.

The case of manual-task intensive occupations (mostly in the Prod-Op-Crafts and Srvc-Care groups) is also in line with the latter general finding. But it seems that the overall demand shift was negative because employment as well as average wages and skill prices declined. One likely reason for this is measurement, since the QCS questionnaires have some difficulty distinguishing between routine and manual job tasks. The other is that alternative demand forces than RBTC have lifted the employment and skill prices of Srvc-Care occupations, despite their high (measure of) manual tasks.[17]

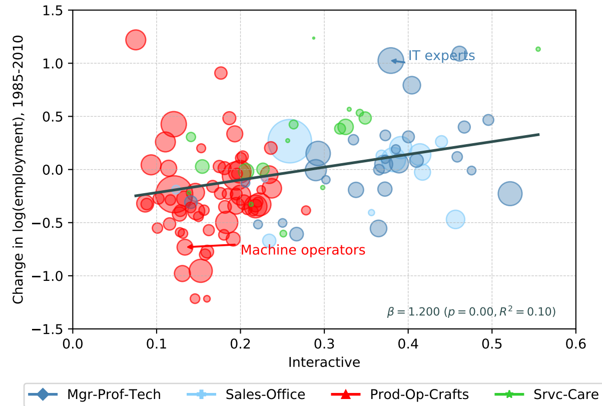
[17] Additional forces that could have worked on Srvc-Care include demand for social skills or consumption of low-skill services (Deming, 2017; Autor and Dorn, 2013; Mazzolari and Ragusa, 2013). In the case of Prod-Op-Crafts occupations, employment may have declined even more than predicted by RBTC because of trade and offshoring (Autor et al., 2013; Goos et al., 2014). See also Footnote 1.

Figure D.15: Correlation of employment changes with task measures

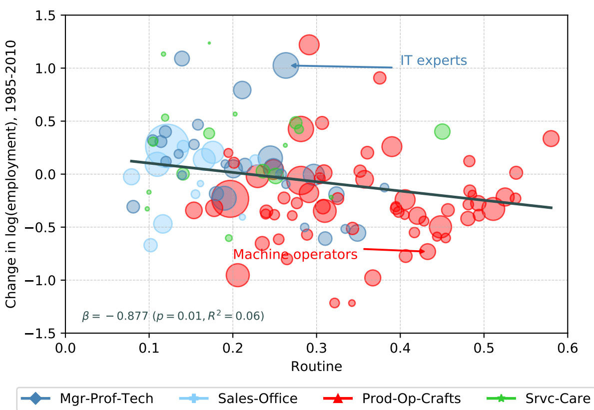
(a) Analytical



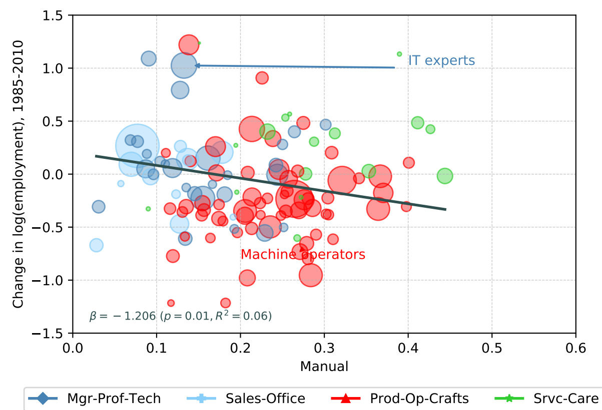
(b) Interactive



(c) Routine

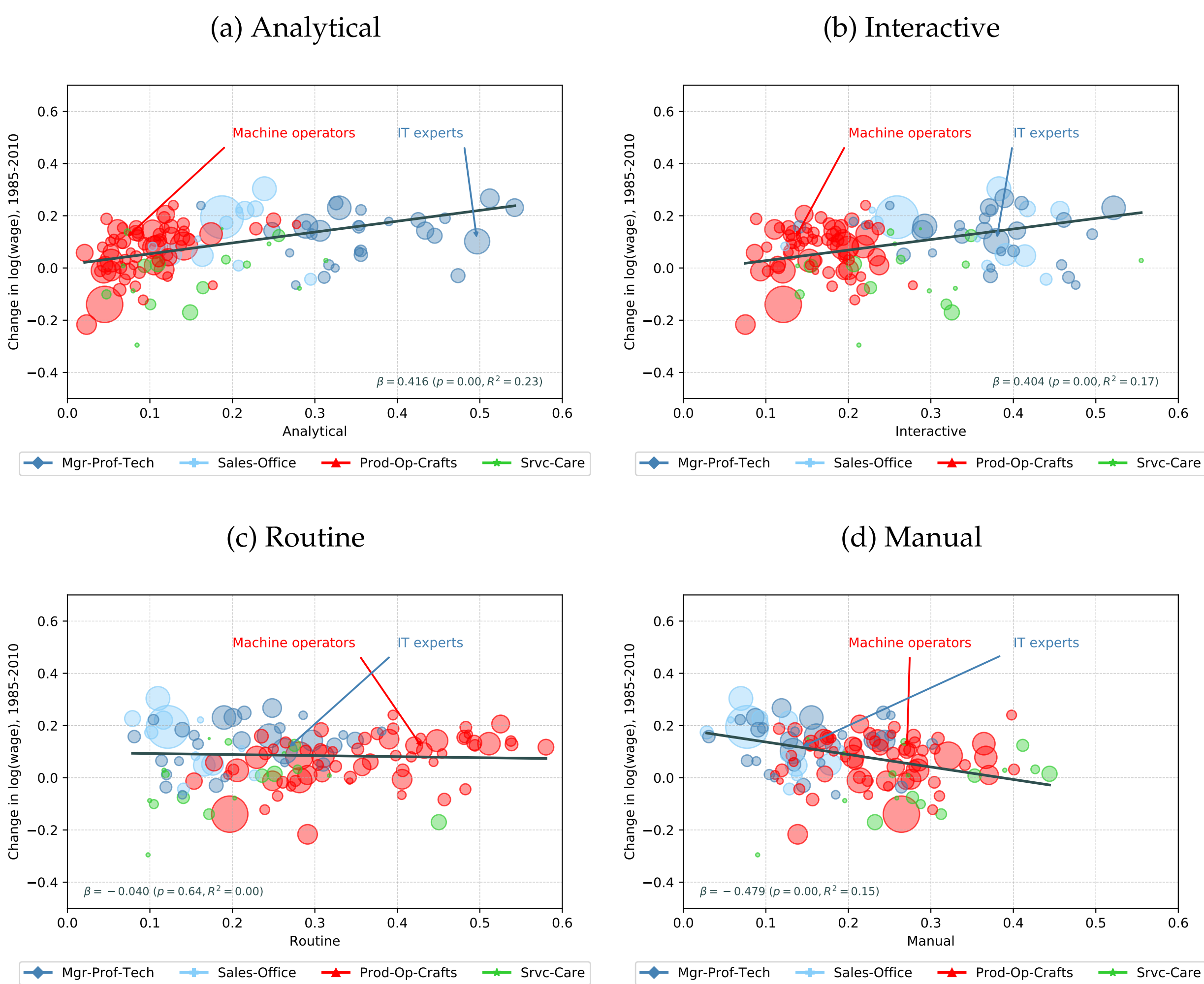


(d) Manual



Notes: The vertical axes in all panels show the change of the log number of employed workers within an occupation between 1985 and 2010. Task measures were computed using the Qualifications and Career Surveys. In the QCS surveys, workers are asked what tasks they perform in their job, e.g. "how often do you repair stuff". They provide answers on a scale: "never, sometimes, often". We assign numerical values $\{0, \frac{1}{3}, 1\}$ to these categories, respectively. We group all the questions into the four categories mentioned in the headers and average over occupations implying that the four task categories do not need to sum up to one as some occupations might be more intense in overall tasks than others. The six different QCS waves were pooled together as the questions are hardly comparable between waves. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

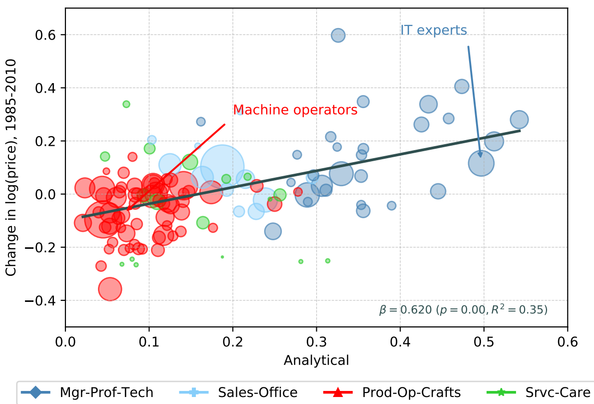
Figure D.16: Correlation of wage changes with task measures



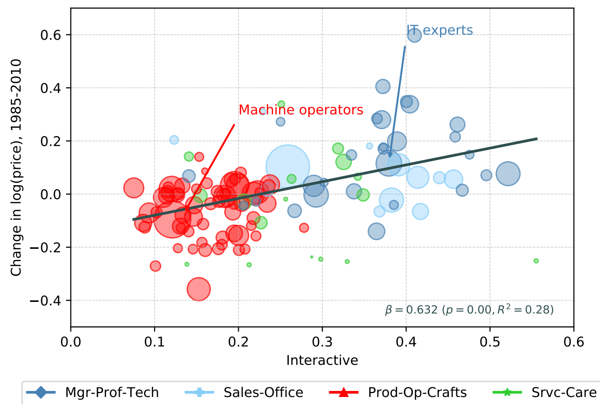
Notes: The vertical axes in all panels show the change of the average log wage within an occupation between 1985 and 2010. Task measures were computed using the Qualifications and Career Surveys. In the QCS surveys, workers are asked what tasks they perform in their job, e.g. "how often do you repair stuff". They provide answers on a scale: "never, sometimes, often". We assign numerical values $\{0, \frac{1}{3}, 1\}$ to these categories, respectively. We group all the questions into the four categories mentioned in the headers and average over occupations implying that the four task categories do not need to sum up to one as some occupations might be more intense in overall tasks than others. The six different QCS waves were pooled together as the questions are hardly comparable between waves. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.17: Correlation of skill price changes with task measures

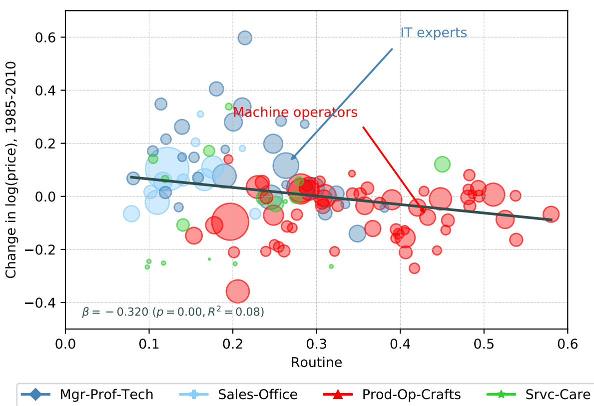
(a) Analytical



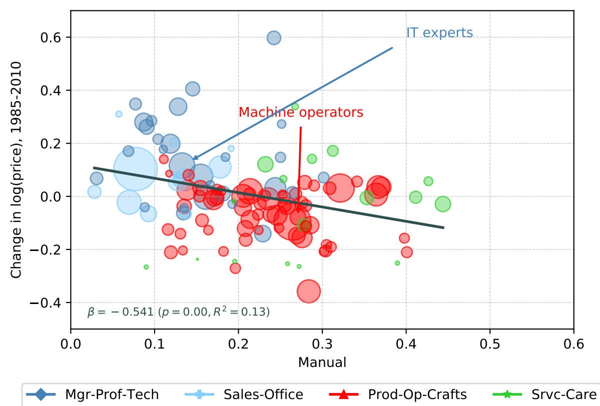
(b) Interactive



(c) Routine



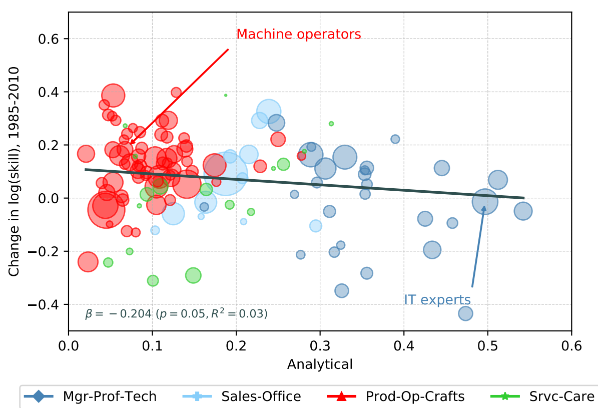
(d) Manual



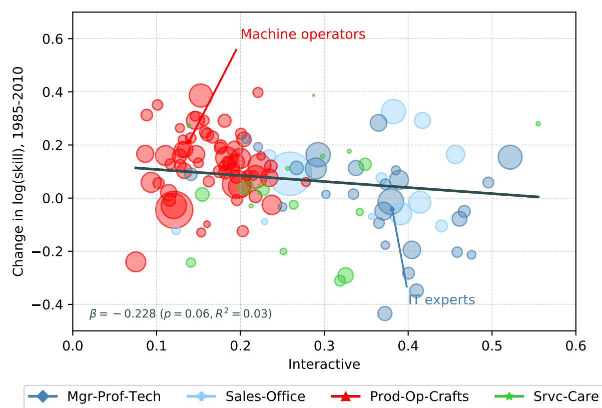
Notes: The vertical axes in all panels show the change of skill prices between 1985 and 2010. OLS estimates as described by Equation (6). Task measures were computed using the Qualifications and Career Surveys. In the QCS surveys, workers are asked what tasks they perform in their job, e.g. "how often do you repair stuff". They provide answers on a scale: "never, sometimes, often". We assign numerical values $\{0, \frac{1}{3}, 1\}$ to these categories, respectively. We group all the questions into the four categories mentioned in the headers and average over occupations implying that the four task categories do not need to sum up to one as some occupations might be more intense in overall tasks than others. The six different QCS waves were pooled together as the questions are hardly comparable between waves. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

Figure D.18: Correlation of skill changes with task measures

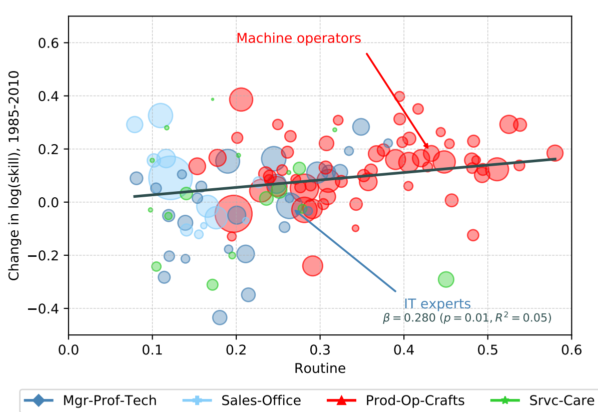
(a) Analytical



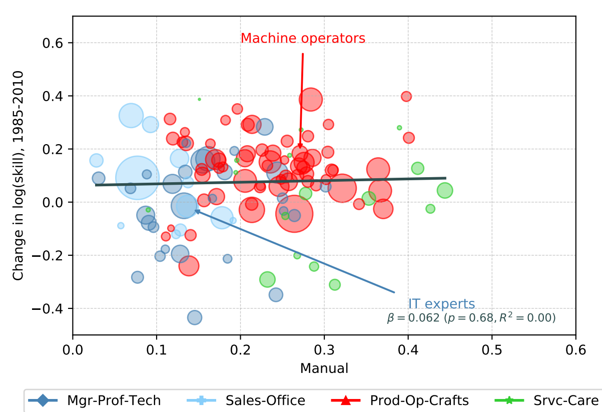
(b) Interactive



(c) Routine



(d) Manual



Notes: The vertical axes in all panels show the change of skills between 1985 and 2010 estimated as the residual between price and wage changes as shown in Equation (8). OLS estimates as described by Equation (6). Task measures were computed using the Qualifications and Career Surveys. In the QCS surveys, workers are asked what tasks they perform in their job, e.g. "how often do you repair stuff". They provide answers on a scale: "never, sometimes, often". We assign numerical values $\{0, \frac{1}{3}, 1\}$ to these categories, respectively. We group all the questions into the four categories mentioned in the headers and average over occupations implying that the four task categories do not need to sum up to one as some occupations might be more intense in overall tasks than others. The six different QCS waves were pooled together as the questions are hardly comparable between waves. One bubble represents one of the 120 detailed occupations in the SIAB SUF. The four groups show an aggregation of these detailed occupations as described in Appendix Table A.1. Bubble size corresponds to the number of employed workers in an occupation averaged across years 1985 until 2010. Regression lines across all occupations (black) and within the four broad groups (colored) are weighted by the number of employed workers.

E Further Details on Wage Inequality

This section provides more details on the analyses of the wage distribution. We begin with the inequality between occupations from Section 5.1. Then we turn to further analyses and robustness checks for the effect of the full estimated model on various wage percentiles and overall inequality.

E.1 Derivations and Further Results on the Attenuating Effect of Selection

We start by deriving the Decomposition (12) of the main text. Note that $\sigma(\bar{w}_{k,t}, \bar{w}_{k,1985}) = cov(\bar{w}_{k,t}, \bar{w}_{k,1985})$, $\sigma^2(\bar{w}_{k,t}) = \sigma(\bar{w}_{k,t}, \bar{w}_{k,t})$, and by the linear additivity of the covariance operator:

$$\sigma^2(\Delta\bar{w}_{k,t}) = \sigma^2(\bar{w}_{k,t} - \bar{w}_{k,1985}) = \sigma^2(\bar{w}_{k,t}) + \sigma^2(\bar{w}_{k,1985}) - 2 \cdot \sigma(\bar{w}_{k,t}, \bar{w}_{k,1985})$$

Rearranging this give the terms under the braces in Equation (12):

$$\begin{aligned}\Delta\sigma^2(\bar{w}_{k,t}) &= \sigma^2(\Delta\bar{w}_{k,t}) - 2 \cdot \sigma^2(\bar{w}_{k,1985}) + 2 \cdot \sigma(\bar{w}_{k,t}, \bar{w}_{k,1985}) \\ &= \sigma^2(\Delta\bar{w}_{k,t}) - 2 \cdot \sigma^2(\bar{w}_{k,1985}) + 2 \cdot \sigma(\bar{w}_{k,1985} + \Delta\bar{w}_{k,t}, \bar{w}_{k,1985}) \\ &= \sigma^2(\Delta\bar{w}_{k,t}) + 2 \cdot \sigma(\Delta\bar{w}_{k,t}, \bar{w}_{k,1985})\end{aligned} \tag{11}$$

Finally, inserting the sum of skill prices and average skills for the average wages (i.e.,$\bar{w}_{k,t} = \pi_{k,t} + \bar{s}_{k,t}$):

$$\begin{aligned}\Delta\sigma^2(\bar{w}_{k,t}) &= \sigma^2(\Delta\pi_{k,t} + \Delta\bar{s}_{k,t}) + 2 \cdot \sigma(\Delta\pi_{k,t} + \Delta\bar{s}_{k,t}, \bar{w}_{k,1985}) \\ &= \sigma^2(\Delta\pi_{k,t}) + \sigma^2(\Delta\bar{s}_{k,t}) + 2 \cdot \sigma(\Delta\pi_{k,t}, \Delta\bar{s}_{k,t}) \qquad , \\ &\quad + 2 \cdot \sigma(\Delta\pi_{k,t}, \bar{w}_{k,1985}) + 2 \cdot \sigma(\Delta\bar{s}_{k,t}, \bar{w}_{k,1985})\end{aligned} \tag{12}$$

where $\bar{s}_{k,t}$ is the average skill in occupation k at time t.

The second panel of Table E.1 restates the results of this decomposition, in the actual data and for the counterfactuals with price changes only, reweighting of the demographic structure, and the combination of the two. This is all the same as in the main text, other than that—at the very right of the table—we add another counterfactual where also the occupation distribution is used for the reweighting. That counterfactual is not much different from the one before where only age, foreigner status, and education are reweighted; as we have also mentioned in the main text.

Within-occupation wage inequality may also be affected by selection into occupations due to changing skill prices. If, for instance, rising prices attract workers of lower skill than the incumbents, inequality will increase within growing sectors. If occupations with high inequality grow, then within inequality will rise overall. Conversely, within inequality might decrease in shrinking occupations with declining skill prices because their low skilled workers may leave. The bottom panel of Table E.1 also shows a decomposition of wage inequality within occupations.

Denote $\tilde{w}_{k,i,t}$ as the difference between an individual's wage and the average wage within his occupation. Given that skill prices are the same for a fixed occupation, this residual wage difference is the same as the residual skill difference: $\tilde{w}_{k,i,t} = \tilde{s}_{k,i,t} = s_{k,i,t} - \bar{s}_{k,t}$. The average within-occupation variance of log wages becomes:

$$\sigma^2(\tilde{w}_{k,i,t}) = \sigma^2(\tilde{s}_{k,i,t}) = \frac{1}{N_t}\sum_{i=1}^{N_t}\tilde{s}^2_{k,i,t} = \sum_{k=1}^{K}\overbrace{\frac{N_{k,t}}{N_t}}^{p_{k,t}}\cdot\overbrace{\frac{1}{N_{k,t}}\sum_{i\in k}\tilde{s}^2_{k,i,t}}^{\sigma^2_{k,t}} = \sum_{k=1}^{K} p_{k,t}\sigma^2_{k,t}, \tag{13}$$

where $p_{k,t}$ is occupation k's share of total employment at time t and $\sigma^2_{k,t}$ is the variance of wages or skills within the occupation. The change of the average within variance is:

$$\begin{aligned}\Delta\sigma^2(\tilde{w}_{k,i,t}) = \Delta\sigma^2(\tilde{s}_{k,i,t}) &= \sum_{k=1}^{K}\left(p_{k,t}\sigma^2_{k,t} - p_{k,1985}\sigma^2_{k,1985}\right)\\ &= \sum_{k=1}^{K}\Delta\sigma^2_{k,t}p_{k,1985} + \sum_{k=1}^{K}\Delta p_{k,t}\sigma^2_{k,1985} + \sum_{k=1}^{K}\Delta\sigma^2_{k,t}\Delta p_{k,t}\end{aligned} \tag{14}$$

Therefore, the rise of within-occupation inequality can be decomposed into terms linked to the changing employment structure and 'pure' increases of the variance of log wages in occupations at fixed sizes. In addition, the last summand of Equation (14) is actually the covariance of changing within inequality with changing employment share. That is, how much the variance of skills in occupations rises for growing occupations, which is related to the declining (rising) skills in growing (shrinking) occupations discussed in Section 4. This relationship generates 0.56 (i.e., $1.34 - 0.78$) log points of the increase in within inequality in the second column, bottom panel of Table E.1.

The other component related to the changing employment structure is the growing size of sectors with high initial within inequality. These are often relatively large occupations inside the rising Mgr-Prof-Tech, Sales-Office, and Srvc-Care groups, which is partly due to the German KLDB occupation classification being more detailed in production and crafts related occupations than in managerial, office, or service type occupations (see Table A.1). The effect of this is the second summand in Equation (14) and it makes up another 0.59 log points of the increase in within-occupation inequality in Table E.1. Clearly the largest part of the rising within variance is the first summand in Equation (14). However, also here the employment structure played a role because larger occupations, which as we said are often in Mgr-Prof-Tech, Sales-Office, and Srvc-Care occupations, had higher increases of within inequality.

The remaining columns in the bottom panel of Table E.1 again show and decompose the effect of the reweighting counterfactuals (notice that the skill prices vary only across occupations and thus have no effect on inequality within). We see that this has an overall modest effect but that additionally reweighting the occupation composition at the very right of the table does raise that effect, since it almost perfectly matches the growth of occupations with large inequality within (i.e., 0.59 in the actual and 0.63 in that counterfactual).

Table E.1: Between-within occupation variance of observed log wages, experiments

		Level 1985	Difference 2010 - 1985							
		Observed	Observed	Prices only	Rew. age, foreign	+ prices	Rew. age, foreign, education	+ prices	Rew. age, foreign, education, occupation	+ prices
Overall	$\sigma^2(w_{i,t})$	14.28	12.41	5.13	0.45	5.70	2.41	9.56	2.70	8.44
Between	$\sigma^2(\bar{w}_{k,t})$	5.03	5.25	5.13	0.34	5.59	1.74	8.88	1.60	7.34
	$2 \cdot \sigma(\Delta\pi_{k,t}, \bar{w}_{k,1985})$		3.23	3.23	0.00	3.23	0.00	3.23	0.00	3.23
	$\sigma^2(\Delta\pi_{k,t})$		1.76	1.89	0.00	1.92	0.00	2.36	0.00	1.79
	$2 \cdot \sigma(\Delta\bar{s}_{k,t}, \bar{w}_{k,1985})$		-0.53	0.00	0.26	0.26	0.53	0.53	0.59	0.59
	$\sigma^2(\Delta\bar{s}_{k,t})$		3.02	0.00	0.07	0.07	1.21	1.21	1.00	1.00
	$2 \cdot \sigma(\Delta\pi_{k,t}, \Delta\bar{s}_{k,t})$		-2.24	0.00	0.00	0.10	0.00	1.55	0.00	0.73
Within	$\sigma^2(w_{i,t} - \bar{w}_{k,t})$	9.25	7.16	0.00	0.11	0.11	0.68	0.68	1.10	1.10
	$\sum_k \Delta\sigma^2_{k,t}\Delta p^{>0}_{k,t}$		1.34	0.00	0.00	0.00	-0.01	-0.01	0.05	0.05
	$\sum_k \Delta\sigma^2_{k,t}\Delta p^{\leq 0}_{k,t}$		-0.78	0.00	-0.00	-0.00	-0.03	-0.03	-0.07	-0.07
	$\sum_k \Delta p_{k,t}\sigma^2_{k,1985}$		0.59	0.00	-0.01	-0.01	0.28	0.28	0.63	0.63
	$\sum_k \Delta\sigma^2_{k,t} p_{k,1985}$		6.02	0.00	0.13	0.13	0.44	0.44	0.49	0.49

Notes: The levels in 1985 are 14.3 (overall), 5.0 (between), and 9.3 (within). Based on specification with 120 occupations. $\bar{w}_{k,t}$ refers to the average wage in occupation k in year t. Values $\times$ 100. The experiments are: Prices only: Take average wages in 1985 and add price changes to simulate 2010's wages. Rew. age, foreign: Take wages in 1985 and reweigh them according to 2010's age and foreign worker distribution with weights computed following DiNardo et al. (1996) to simulate 2010's wages. + prices: add price changes on top.

E.2 Additional Results for the Scenarios from the Full Model

Here, we first provide the explicit formulas for the scenarios in Figure 8. We then describe some features of the table and figures in this section. These include the levels of the percentiles and the variance in the data and under the model prediction (Table E.2). They also include two different sample/data preparation specifications (Figures E.1 and E.2), and a permutation of the order in which we add the components of the model (Figure E.3).

The first scenario in Figure 8c reports the trend of inequality that would prevail if only the wage distribution at age 25 (or an older age for later entrants) had shifted, with changes in skill prices as well as skill accumulation or occupation-switching over the life-cycle turned off. That is,

$$\hat{w}_{i,t}^{\text{Initial occupation and wage throughout}} = w_{i,t_{i,0}}, \tag{15}$$

where $t_{i,0} \leq t$ denotes the year when worker i joins the labor market.

The next scenario adds skill accumulation to these initial wages. In particular, Figure 8d shows the inequality due to changing initial occupation distribution (measured by $I_{k,i,t_{i,0}}$), age structure of employment ($X_{i,\tau-1}$), and associated changes of skill accumulation over time ($\hat{\Gamma}_{k,k}$):

$$\hat{w}_{i,t}^{\text{Initial occupation + skill accumulation}} = w_{i,t_{i,0}} + \sum_{\tau=t_{i,0}+1}^{t} I_{i,\tau-1} \cdot \Gamma_{a(i,\tau-1),k(i,t_{i,0}),k(i,t_{i,0})}, \tag{16}$$

where the worker joined the labor market at time $t_{i,0} \leq t$, never switches (i.e., the $k(i, t_{i,0})$ index is fixed), and $I_{i,\tau-1}$ indicates whether the worker was employed in $\tau - 1$. That is, we assume that skills stagnate during non-employment spells. Also, workers who are currently unemployed or out of the labor force do not enter any of the scenarios.

The scenario in Figure 8e includes occupation switching, but leaves out the skill changes associated with switching. The wage in this scenario becomes:

$$\hat{w}_{i,t}^{\text{Observed occ. + skill acc.; }\Gamma_{a,k,l\neq k}=0} = w_{i,t_{i,0}} + \sum_{\tau=t_{i,0}+1}^{t} I_{i,\tau-1} I_{k(i,\tau)=k(i,\tau-1)} \cdot \Gamma_{a(i,\tau-1),k(i,\tau-1),k(i,\tau)} \tag{17}$$

Here $I_{k(i,\tau)=k(i,\tau-1)}$ is an indicator variable that the worker stayed in his $\tau - 1$ occupation. Again, $I_{i,\tau-1}$ is zero if the worker was unemployed or out of the labor force in the respective period. We do assign workers who return from non-employment one $\Gamma_{a(i,\tilde{\tau}),k(i,\tilde{\tau}),k(i,\tilde{\tau})}$, with $\tilde{\tau}$ the period before the spell, for their previous occupation, however. In the scenarios with the gains from switching immediately below we assign $\Gamma_{a(i,\tilde{\tau}),k(i,\tilde{\tau}),k}$ for their previous $k(i, \tilde{\tau})$ and current k occupation combination. Either of this does not make a material difference for the results and, for ease of notation, it is not explicitly indicated in the formulas.

The next scenario adds the skill changes associated with switching in Figure 8f. The wage in this scenario becomes:

$$\hat{w}_{i,t}^{\text{Observed occ. + skill accumulation}} = w_{i,t_{i,0}} + \sum_{\tau=t_{i,0}+1}^{t} I_{i,\tau-1} \cdot \Gamma_{a(i,\tau-1),k(i,\tau-1),k(i,\tau)} \tag{18}$$

Finally, we add our estimated skill prices in Figure 8b. The wage in the full empirical model becomes:

$$\hat{w}_{i,t}^{\text{Model}} = w_{i,t_{i,0}} + \sum_{\tau=t_{i,0}+1}^{t} \Delta\pi_{\tau,k(i,\tau)} + \sum_{\tau=t_{i,0}+1}^{t} I_{i,\tau-1} \cdot \Gamma_{a(i,\tau-1),k(i,\tau-1),k(i,\tau)} \tag{19}$$

Features of the tables and figures in this section: As detailed in the main text, we consider two different specifications in this section. First, to partly abstract from the supply shock of increased migration after 1990, we exclude anybody ever excluded as a foreigner. Second, we fill non-employment spells to see how periods in unemployment or outside of the labor force impact the scenarios. For the latter, all notes related to these spells in the formulas (15)–(19) are irrelevant here.

Since Figure 8 showed the evolution of the three percentiles under consideration normalized to zero in 1985, we display their 1985 levels in Table E.2 along with the variance. Across all scenarios, the model fits the levels well. None of the values deviates by more than 1.5/100 from the actual value. This is quite remarkable given that the estimation of the model targets average occupational wages for demographic groups. The predictions for the differences between the endpoints of our study period are also broadly in line with the data.

Figure E.1 shows the same scenarios as Figure 8 in the main text when excluding anybody who was ever coded as a foreigner from the sample. The most important fact to note is that in Panel c, the decline in the 15$^{\text{th}}$ percentile is not nearly as pronounced as in Figure 8c. In the experiment where unemployment is a choice (Figure E.2), the same broad conclusions hold as in the main text. Some differences are noteworthy, however. Already in the data, the 15$^{\text{th}}$ percentile decreases much more than in Figure 8a, the pattern is similar but much less pronounced for the higher percentiles. In this specification, price changes hurt both the median and the 15$^{\text{th}}$ percentile; the latter actually slightly loses from switching (Panels e $\rightarrow$ f). This highlights that we overestimate the gains from switching at the lower end because occupation changes involving wage losses often go via an unemployment spell.

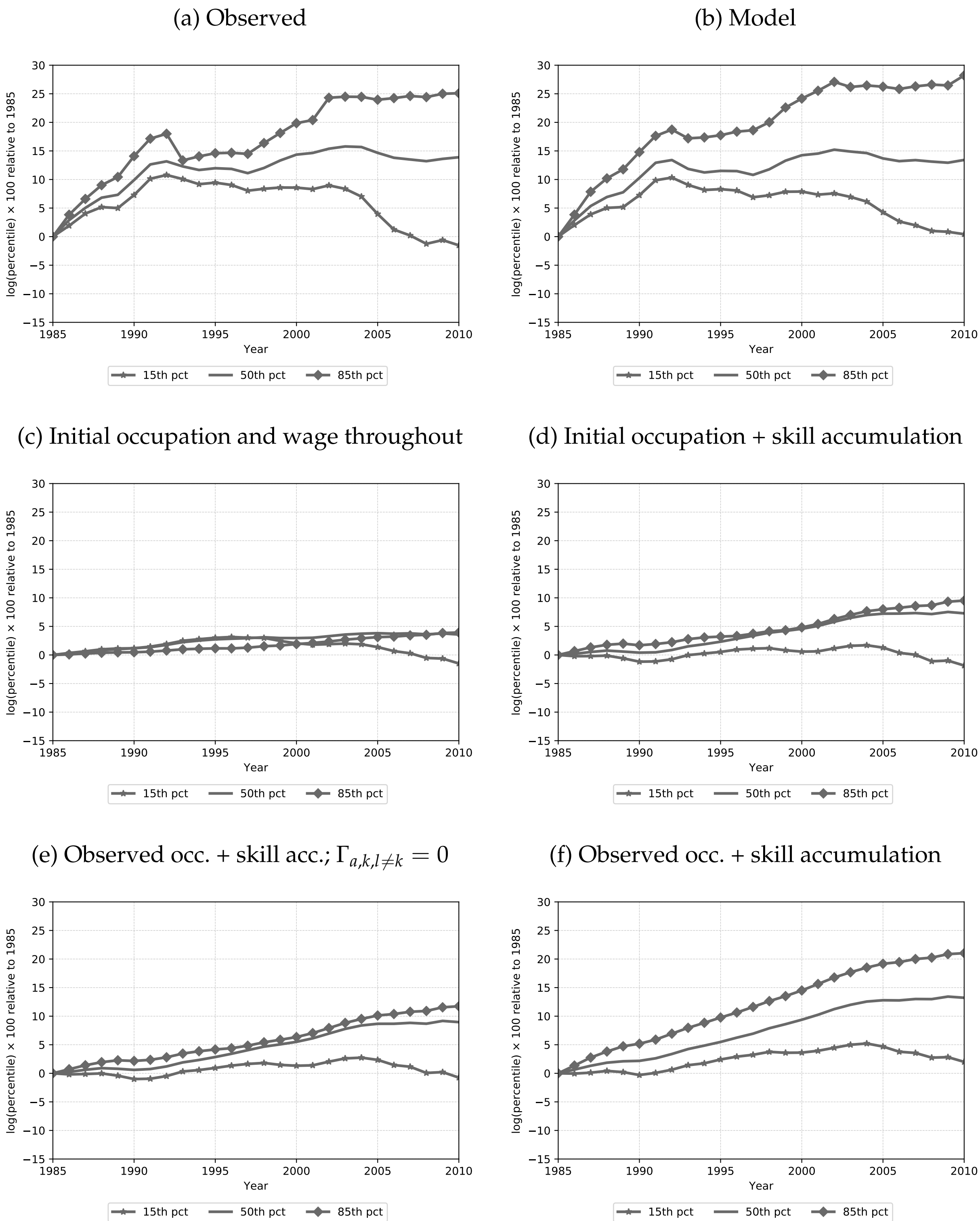
Finally, note that the sequencing of the experiments in Figure 8 is arbitrary. In fact, the sequencing only matters with respect to when occupation switching is added because, conditional on occupation choice, all other components enter separately and do not interact. In Figure E.3, we add prices immediately to the initial wages and add occupation switching as late as possible. Interestingly, all three percentiles would have evolved in almost the same way until the mid-nineties and they opened up only afterwards. Adding skill accumulation then yields the more familiar pattern, which is opened up further by switches.

Table E.2: Levels of wage percentiles and the variance for model and sample specifications

		Main sample		Filled non-employment spells		Anybody ever coded as foreign excluded	
		Level 1985	Diff. 2010 - 1985	Level 1985	Diff. 2010 - 1985	Level 1985	Diff. 2010 - 1985
High	Data	1080.71	24.03	1079.12	23.27	1081.42	25.09
$\log(p_{85})$	Model prediction	1082.38	26.86	1080.00	23.27	1082.73	28.21
Median	Data	1042.88	11.55	1041.27	9.75	1043.14	13.89
$\log(p_{50})$	Model prediction	1044.48	11.63	1041.65	5.96	1044.78	13.42
Low	Data	1017.07	-5.13	1013.23	-10.53	1017.78	-1.52
$\log(p_{15})$	Model prediction	1015.95	-2.23	1011.46	-11.51	1016.36	0.43
Variance	Data	14.28	12.41	16.48	15.59	14.20	11.21
$\sigma^2(w_{i,t})$	Model prediction	14.66	12.11	16.41	15.22	14.63	10.91

Notes: The table shows observed levels of the 85th, 50th and 15th log wage distribution percentiles as well as the variance of log wages in 1985 and changes between 2010 and 1985. All values $\times$ 100. In addition, the table shows model predictions of levels and changes according to Equation (19). The first two columns show the results for the baseline sample. Columns three and four present the results when we also drop workers which are reported to be foreigners at some point in time. This includes, for instance, workers acquiring the German nationality at some later point in the life cycle. For the last two columns, unemployment and out of labor force spells are imputed by comparing the (real) wage after a non-employment spell with the wage before the non-employment spell. We then fill up the wage while in non-employment as the lower of those two wages adjusted for inflation and set the occupation within this time to the occupation that corresponds to that lower wage. See Appendix A.1.4 for the details.

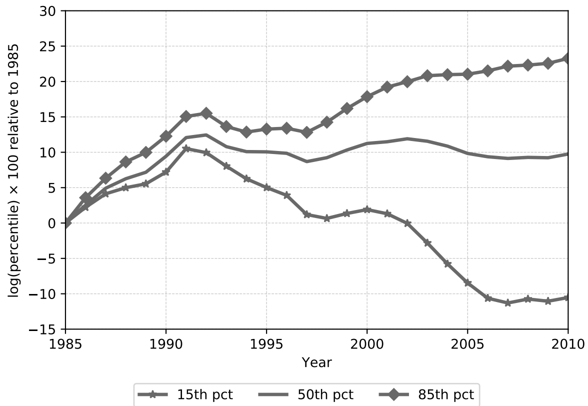
Figure E.1: Wage inequality scenarios, anybody ever coded as foreign excluded



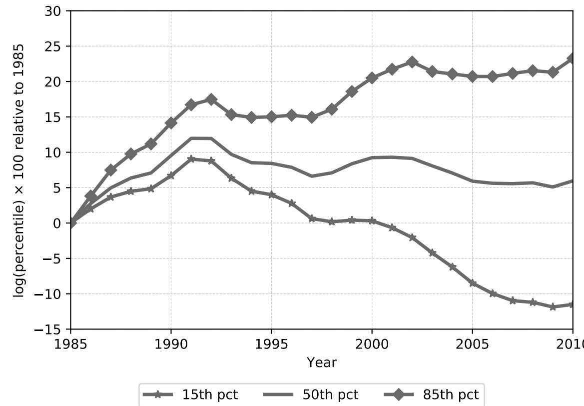
Notes: Panel a: Observed wages. *Panel b*: Simulated life-cycle trajectories based on our full model: Starting from the initial wage and occupational choice, add all skill accumulation and price change estimates using occupational choices observed in the data. *Panel c*: Workers keep their initial wage throughout the life cycle. *Panel d*: Workers stay in their initial job throughout the life-cycle; in each period, we add the skills they would have accumulated in that job (i.e., $\Gamma_{a(i,t_{i,0}),k(i,t_{i,0}),k(i,t_{i,0})}$). *Panel e*: Use observed switches, setting direct gains from switching to zero, i.e., $\Gamma_{a(i,t-1),k(i,t-1),k} = 0 \; \forall \; k \neq k(i,t-1)$. Price changes are zero as well, so the difference to Panel d comes purely from differential skill accumulation in occupations. *Panel f*: As in Panel e, but adding the direct gains from switching. The only difference to the full model in Panel b are the price changes, which continue to be zero. In all scenarios, we treat unemployment or out-of-the-labor force spells as follows: When such a spell is observed in the data, simulated workers do not enter the inequality statistics. Further, we assume no depreciation and upon re-entry into paid work add—where relevant—$\Gamma_{a(i,\tilde{t}),k(i,\tilde{t}),k}$ with $\tilde{t}$ the period before the spell. The sample is the same as the baseline sample except that we also drop workers which are reported to be foreigners at some point in time. This includes, for instance, workers acquiring the German nationality at some later point in the life cycle.

Figure E.2: Wage inequality scenarios, filled non-employment spells

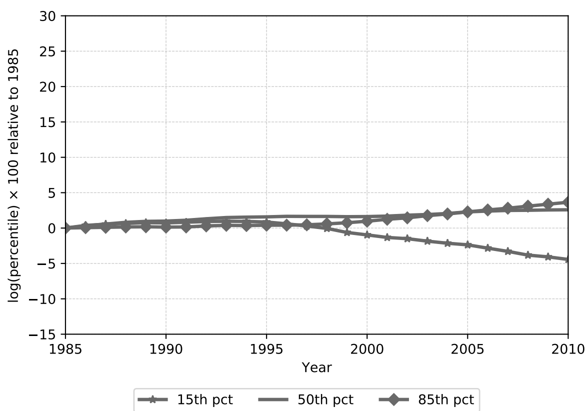
(a) Observed



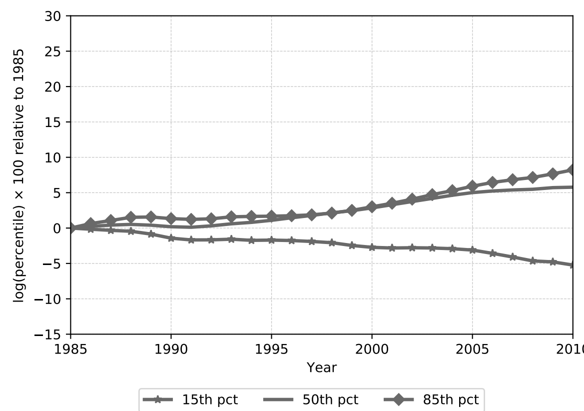
(b) Model



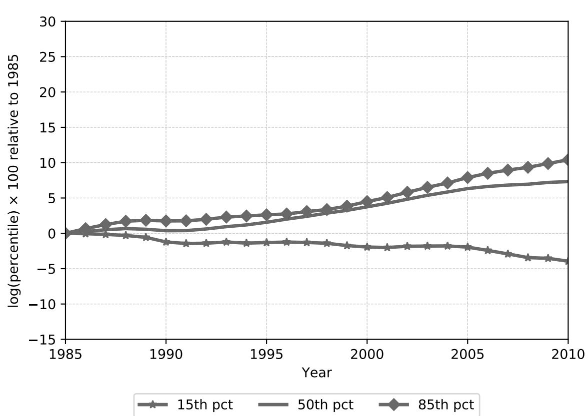
(c) Initial occupation and wage throughout



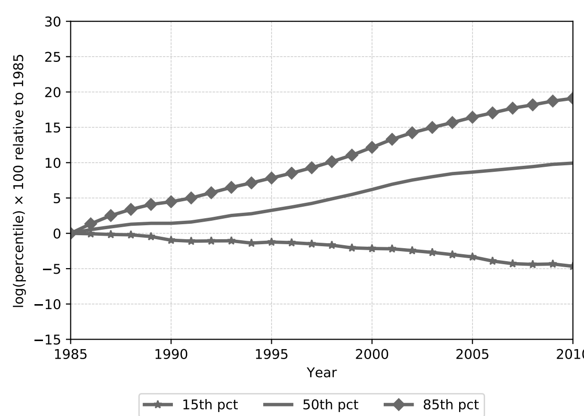
(d) Initial occupation + skill accumulation



(e) Observed occ. + skill acc.; $\Gamma_{a,k,l\neq k} = 0$

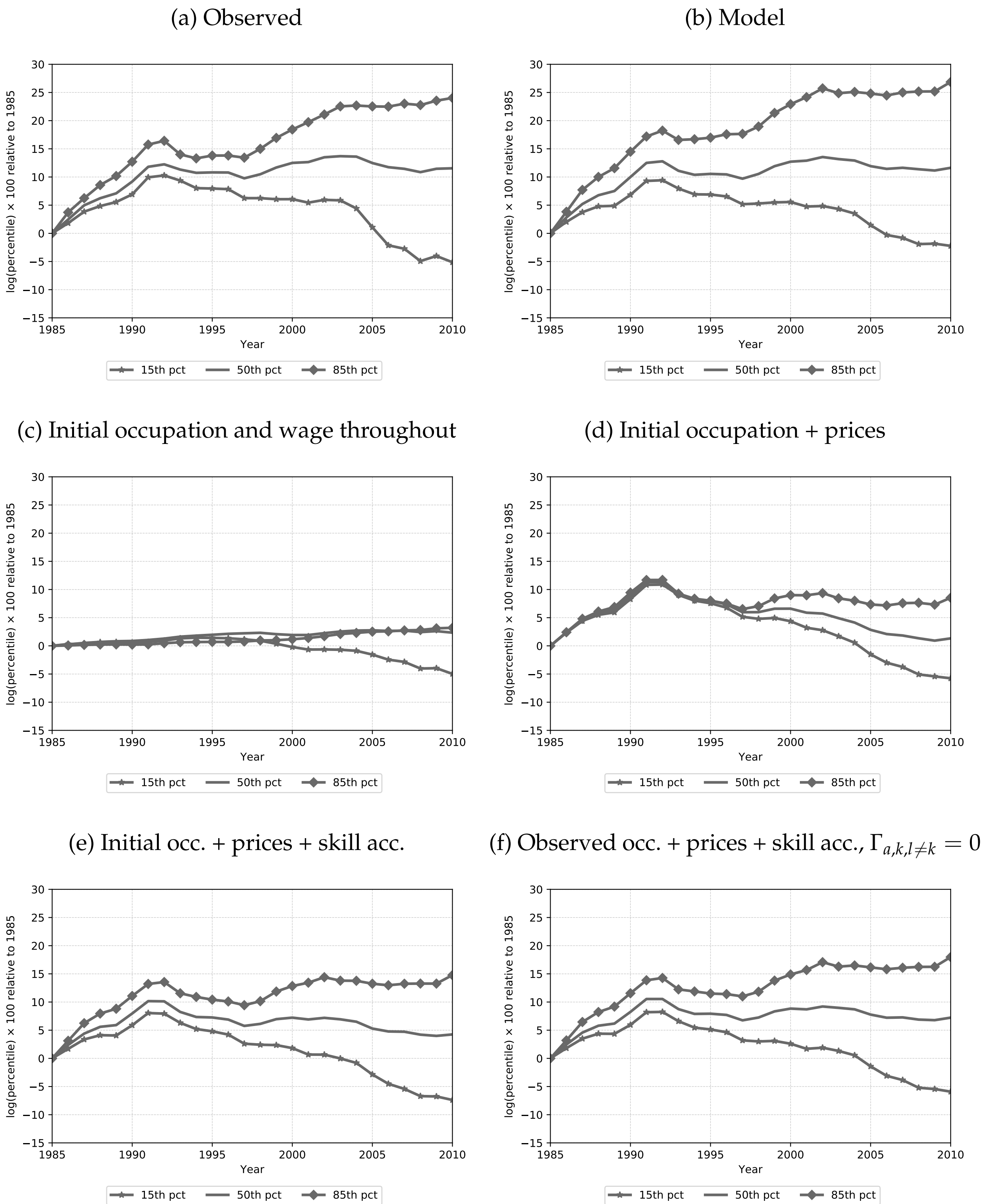


(f) Observed occ. + skill accumulation



Notes: Panel a: Observed wages. *Panel b*: Simulated life-cycle trajectories based on our full model: Starting from the initial wage and occupational choice, add all skill accumulation and price change estimates using occupational choices observed in the data. *Panel c*: Workers keep their initial wage throughout the life cycle. *Panel d*: Workers stay in their initial job throughout the life-cycle; in each period, we add the skills they would have accumulated in that job (i.e., $\Gamma_{a(i,t_{i,0}),k(i,t_{i,0}),k(i,t_{i,0})}$). *Panel e*: Use observed switches, setting direct gains from switching to zero, i.e., $\Gamma_{a(i,t-1),k(i,t-1),k} = 0 \; \forall \; k \neq k(i,t-1)$. Price changes are zero as well, so the difference to Panel d comes purely from differential skill accumulation in occupations. *Panel f*: As in Panel e, but adding the direct gains from switching. The only difference to the full model in Panel b are the price changes, which continue to be zero. Unemployment and out of labor force spells are imputed by comparing the (real) wage after a non-employment spell with the wage before the non-employment spell. We then fill up the wage while in non-employment as the lower of those two wages adjusted for inflation and set the occupation within this time to the occupation that corresponds to that lower wage. See Appendix A.1.4 for the details.

Figure E.3: Wage inequality scenarios, order prices → accumulation → switching



Notes: Panel a: Observed wages. *Panel b*: Simulated life-cycle trajectories based on our full model: Starting from the initial wage and occupational choice, add all skill accumulation and price change estimates using occupational choices observed in the data. *Panel c*: Workers keep their initial wage throughout the life cycle. *Panel d*: Workers stay in their initial job throughout the life-cycle; in each period, we add the price changes estimates in that job (i.e., $\Delta\pi_{k_0,t}$). *Panel e*: In addition to Panel d, add differential skill accumulation in occupations. *Panel f*: As in Panel e, but take observed occupational choices as opposed to initial choices. In all scenarios, we treat unemployment or out-of-the-labor force spells as follows: When such a spell is observed in the data, simulated workers do not enter the inequality statistics. Furthermore, we assume no depreciation and upon re-entry into paid work add—where relevant—$\Gamma_{a(i,\tilde{t}),k(i,\tilde{t}),k}$ with $\tilde{t}$ the period before the spell.

E.3 Effect of Skill Accumulation on Wage Percentiles

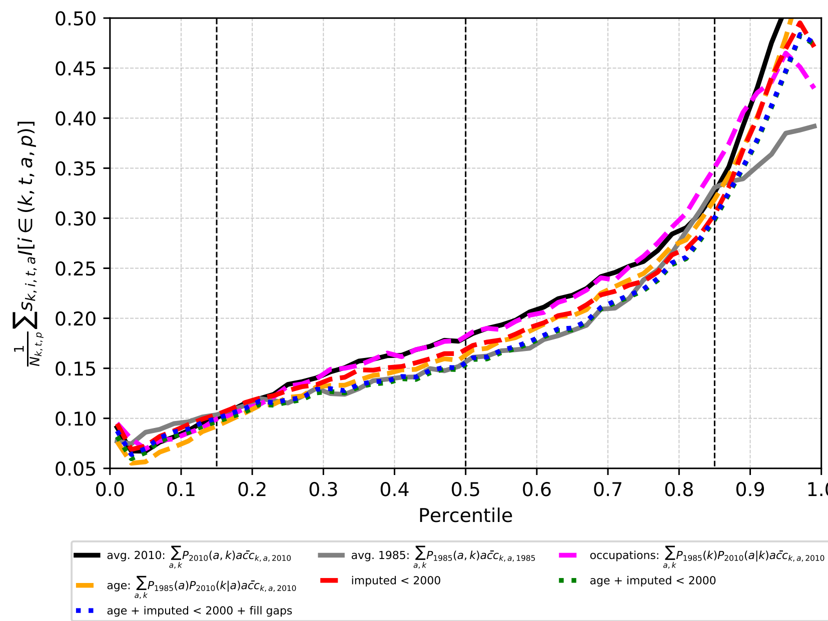
This section analyzes the reasons for skill accumulation's substantial effect on the change of lower-half inequality, also in comparison to its modest effect on the upper-half. To do this, we rewrite the overall skill accumulation as a function of average skill accumulation within detailed worker cells times the frequency of these cells. In particular, for every percentile of the wage distribution in a given year, we compute the average skill accumulation in each worker cell defined by age and initial occupation. Then we average over these cells by their shares in the respective percentiles. That is, we compute the average skill accumulation in each percentile had workers stayed in the occupation of when they first joined the labor market as:

$$avg_t = \sum_{k=1}^{120} \sum_{a=25}^{54} P_t(a,k) \cdot \overline{acc}_{k,a,t} \text{ with} \tag{20}$$

$$\overline{acc}_{k,a,t} = \frac{1}{N_{k,a,t}} \sum_{i \epsilon \{k,a,t\}} \sum_{\tau=t_{i,0}+1}^{t} I_{i,\tau-1} \cdot \Gamma_{a(i,\tau-1),k(i,\tau-1),k(i,\tau)}, \tag{21}$$

where in the second equation $\sum_{i\epsilon\{k,a,t\}}$ is a shorthand for summing over all workers of age a in year t whose initial occupation was k, and $N_{k,a,t}$ is the total number of such workers. As before, $t_{i,0} \leq t$ denotes the year when worker i joins the labor market. In Equation (20) we then weigh by the relative cell sizes $P_t(a,k)$ to obtain the average skill accumulation in the respective wage percentile.[18]

Figure E.4: Skills accumulated during working life by percentile of wage distribution



Notes: Estimates for average skill accumulation obtained in the population by year and percentile in the wage distribution following Equations 20, 21 and 22.

[18] An index for the specific wage percentile is omitted, since this is always conditioned on anyway.

The black solid line in Figure E.4 depicts this average skill accumulation across the percentiles of the 2010 wage distribution. We can see that skill accumulation's contribution to log wages is substantially higher at the median than at the bottom of the distribution, and much higher at the top of the distribution. The gray solid line depicts the corresponding skill accumulation for the year 1985, which is substantially flatter in its lower half but comparably steep as the 2010 skill accumulation between the 50th and the 85th percentile. The difference between the two lines is the effect of the accumulation (i.e., Equation (16) compared to the scenario with only initial wages changing in Equation (15)).

Using Equations (20)–(21), we now decompose the difference between the 2010 and 1985 skill accumulation effect into its parts with a particular focus on the lower half. One obvious component of this is supposed to be the changing occupation structure. Using Bayes' law, we compute the accumulation that would have prevailed if (conditionally) the age structure and within-cell accumulation changed over time but the (initial) occupation structure had stayed the same as in 1985:

$$avg_{2010}(occup = 1985) = \sum_{k=1}^{120} \sum_{a=25}^{54} P_{1985}(k) \cdot P_{2010}(a|k) \cdot \overline{acc}_{k,a,2010} \tag{22}$$

The pink dashed line depicts this skill accumulation, showing that it actually does not explain any of the increase in lower-half inequality. The reason for this rather surprising result is that the occupation structure actually did not shift decidedly toward higher-accumulation occupations at the median. Figure E.5 depicts the corresponding graph in the scenario at hand, i.e., with workers' initial occupations in the distribution of wages only due to entry and skill accumulation. We see that there are the same share of high-accumulation occupations at the median in 1985 as in 2010.[19]

The next potential component of the skill accumulation effect is the shifting age structure in the different parts of the wage distribution. That is, we change the unconditional age distribution at each percentile to its 1985 value but hold the accumulation and the conditional occupation structure at their 2010 values:

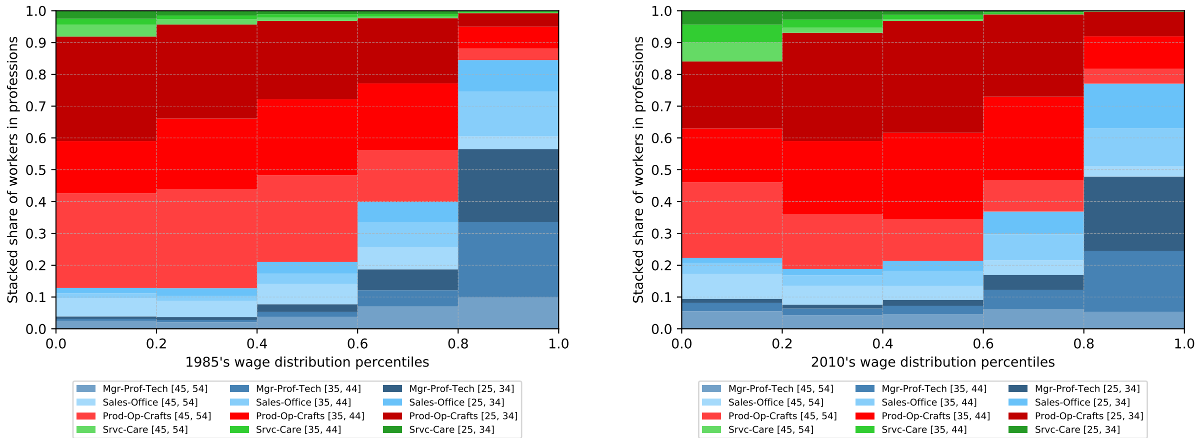
$$avg_{2010}(age = 1985) = \sum_{k=1}^{120} \sum_{a=25}^{54} P_{1985}(a) \cdot P_{2010}(k|a) \cdot \overline{acc}_{k,a,2010} \tag{23}$$

The yellow dashed line in Figure E.4 shows that this strikingly explains more than half of the accumulation effect. In particular, the many experienced workers at the 2010 median, already mentioned in the main text, have accumulated a lot of skills over their careers. Figure E.5 illustrates this even more clearly in the scenario at hand: the share of 45–54 (but also 35–44) year old Prod-Op-Crafts workers at the median is very large in 2010 and much higher than in 1985. Hence, if we down-weigh the share of these workers to 1985 and hold everything else constant, as we do in Equation (23), skill accumulation at the median is substantially lower. Therefore, the large

[19] Admittedly, this may also partially be a reflection of data limitations here, since we need to approximate initial occupations in 1985 by their 1975 occupations for workers who joined the labor market before that (see also discussion further below). That is, some (middle-aged or older) 'blue' Mgr-Prof-Tech or 'Sales-Office' workers in 1985 may have started in the 'red' or 'green' occupations before 1975. This would also explain the higher share of 'blue' initial occupations at the top quintile of the Figure E.5 wage distribution in 1985 than in 2010 and the concurrent stronger 85th percentile increase in the pink 1985 occupation structure series of Figure E.4.

Figure E.5: Shares in the wage distribution by quintile

(a) 1985 (b) 2010



Notes: Each rectangle is proportional to the share of workers in the respective occupation × age bin. Wage quintiles were computed with wages computed as in Equation (16), i.e. wage growth only occurring because of skill accumulation.

baby boomer birth cohorts, who still started their careers in Prod-Op-Crafts occupations,[20] are substantially raising median wages at the end of our analysis period. Bottom wage earners in 2010 are in contrast much younger, and therefore skill accumulation due to demographic change raises lower-half wage inequality in this point in time.

The last factor that may have changed between 1985 and 2010 is the skill accumulation within worker-cells, which we analyze by computing:

$$avg_{2010}(accum = 1985) = \sum_{k=1}^{120} \sum_{a=25}^{54} P_{2010}(a,k) \cdot \overline{acc}_{k,a,1985}. \tag{24}$$

This counterfactual represents a specific version of changing worker employment biographies: since we condition on a fixed initial occupation and age, it can only differ when workers on average have more or less gap years of not working or different ages at labor market entry in 1985 than in 2010. In Equation (21) above, the former corresponds to differences in the number of $I_{i,\tau-1} = 0$ instances (e.g., due to unemployment) and the latter to differences in the total number of years $t - t_{i,0}$ over which skill accumulation is summed for a given age.

The differences in labor market entry ages are hard to measure in our data because we have to impute them for workers who joined the labor market before the beginning of our sample in 1975, that is, who already appear in the 1975 data aged older than 25. We do this by computing, for every occupation, the average entry age across all years from 1976 onward and assign this as the entry age together with their 1975 occupation to every worker who appears in the sample older than 25 in that year. We then impute the wage at labor market entry by subtracting the respective skill accumulation coefficients back to that entry age. This imputation, which affects our

[20]The baby boom in Germany started later than in the U.S., with cohorts comprising birth years 1955–69, i.e., 41–55 year olds in 2010.

computed 1985 (but not 2010) skill accumulation,[21] may generate a bias. We assess this possibility by pretending we only observed 2010 workers' labor market histories after 2001 (i.e., as in 1985, everything longer than nine years ago is unobserved) and then conducting the same imputation.[22]

Since the red dashed line is below the solid black line, Figure E.4 shows that the imputation does indeed underestimate the skill accumulation in 2010, especially at and above the median. Therefore, part of our measured skill accumulation effect on lower-half inequality between 2010 and 1985 may be due to this data issue. Nonetheless, if we apply our calculation (23) on top of the imputed labor market biographies in 2010, age structure differences between the beginning and the end of the analysis period still have a substantial effect on 50–15 inequality. In fact, the combination of imputation and age structure (green dotted line) is almost exactly the same as the actual 1985 skill accumulation in the lower half of the wage distribution.

Finally, we examine the effect of potentially more intermittent prior labor market attachment at either end of the analysis period. That is, similar to Section D.2 we fill up gaps in employment biographies (e.g., due to unemployment) during the nine years leading up to 1985 and 2010, respectively. The dotted blue line shows the results and that actually this has no discernible effect on skill accumulation in addition to the imputation and the age structure effect. In unreported analyses, we found that labor market biographies were indeed somewhat more intermittent leading up to 2010 than 1985, but this only affected the very bottom of the wage distribution (below the 5th percentile) and turns out quantitatively unimportant here.

To summarize the overall result, had we plotted

$$avg_{2010}(age = 1985, accum = 1985) = \sum_{k=1}^{120} \sum_{a=25}^{54} P_{1985}(a) \cdot P_{2010}(k|a) \cdot \overline{acc}_{k,a,1985} \tag{25}$$

into the Figure E.4, it would have almost exactly overlapped with the green dotted line. This implies that the workforce's changing age structure was the main driver of rising lower-half inequality. There is in fact no role for the occupation distribution at labor market entry *conditional on* the age structure (i.e., replacing $P_{2010}(k|a)$ with its 1985 value does not matter for the lower half). Replacing $\overline{acc}_{k,a,1985}$ with a version of $\overline{acc}_{k,a,2010}$ in which initial occupations and wages are imputed as in 1985 also gives the same result (which is the green dotted line). On top of that, filling labor market biographies during the preceding nine years also does not matter (blue dotted line). Therefore, some of the lower-half inequality effect may or may not be attributed to changing initial wages instead of skill accumulation, but the economically and quantitatively important part is accounted for by aging of the workforce.

[21] Given that workers exit the sample at age 54, after the year 2003 nobody is imputed anymore.

[22] Conversely, we have also not imputed at all and taken the first observed wage as the initial one, which actually decreased 50–15 differences in 1985 and thus modestly raised the increase of lower-half inequality in the $\hat{w}^{e}_{i,t}$ scenario (i.e., lowered the part that changing skill accumulation accounts for).

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