Which Ladder to Climb? Decomposing Life Cycle Wage Dynamics*

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Abstract

Wages grow and become more unequal as workers age. Economic theory focuses on worker investment in human capital, search for employers, and residual wage shocks to account for these life cycle wage dynamics. We highlight the importance of jobs: collections of tasks and duties defined by employers within the production process. We provide empirical evidence that climbing the career ladder toward jobs characterized by more responsibility, complexity, and autonomy accounts for the largest part of life cycle wage dynamics. It accounts for 50% of average wage growth, 50% of rising differences between gender, and virtually all of rising dispersion within gender over the life cycle.

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1 Introduction

Wages grow and become more unequal as workers age. Economic theory focuses on worker investment in human capital, labor market search for good employers, and residual wage shocks to account for these life cycle wage dynamics. This paper explores differences in jobs as an alternative to account for observed wage dynamics.

Jobs describe combinations of tasks and duties defined by employers to organize the production process. Job levels provide a summary of the responsibility, complexity, and autonomy of a job's task and duties on a one-dimensional hierarchical scale. Over the life cycle, workers progress (differently) in their careers across job levels; some are promoted while others are not. In the administrative data, these career ladder dynamics account for the largest part of life cycle wage dynamics in Germany. Exploring independent data from Germany and the United States, we provide corroborating evidence demonstrating that job levels in fact account for the largest part of cross-sectional wage differences in the macroeconomy. The finding that wages are attached to jobs more than to workers or employers concurs with a theory in which human capital investment is a necessary rather than sufficient condition for higher wages and where a key difference across employers lies in their organizational structure of their production process. Under this view, the career ladder provides an intimate link between life cycle wage growth and rising wage dispersion.

The importance of jobs and the career ladder for life cycle wage dynamics has been left underexplored in existing research because job levels offering information on vertical job differentiation are not recorded in most employer-employee data (see Section 1.1 for related literature). We explore data from three waves of the German Structure of Earnings Survey (SES) from 2006 to 2014 that offer such information on job levels. For these administrative data, we document that climbing the career ladder accounts for 50% of wage growth and almost all of the increase in wage dispersion over the life cycle. The career ladder is also instrumental in understanding differences in gender wage dynamics; the gender wage gap by age parallels a rising gender career gap by age. We complement these results with evidence from two other data sources, the U.S. National Compensation Survey (NCS) and the German BIBB/BAuA Employment Survey. Both datasets provide detailed information on job requirements and support the finding that differences in job characteristics account for the largest part of wage dispersion across workers and employers in the macroeconomy. In the NCS data, job characteristics account for 75% of the cross-sectional wage dispersion and about half of the within-occupation wage dispersion. Hence, the importance of jobs in accounting for wage differences is a particularity neither of the administrative data nor of the German labor market.

When turning to the determinants of career progression, we find that human capital investments foster it and constitute almost a necessary condition for wage growth; yet, it is not a sufficient condition as a more simple human capital theory would assume. In addition, we provide evidence for the role of organizational structure and luck in career progression. The presence of an older peer (*silverback*) as a competitor for promotion in a plant significantly hinders career progression. Finally, using data from the German Socio-Economic Panel (SOEP), we look at labor market mobility across employers and provide evidence that employer mobility is associated with career progression. However, we also document that most steps on the career ladder happen while staying with the same employer.

Our main data source are the 2006, 2010, and 2014 SES waves, each a large administrative employer-employee dataset representative of the universe of employees and employers, working at plants with at least 10 employees. The database contains roughly 6 million employee observations from 100,000 plants across survey years. The data report the actual (virtually uncensored) pay and hours worked of employees and include detailed information on workers' education, occupation, age, and tenure. In addition, they provide information on job levels. Taken together, all information on jobs, employers, and workers account for over 80% of the observed cross-sectional variation in wages.[1] Dummies for five job levels alone account for more than 45% of cross-sectional wage variation.

While the SES data offer information on job levels, we face the challenge that the data come as repeated cross sections. To control for unobserved heterogeneity when decomposing life cycle wage dynamics, we apply synthetic panel methods (Deaton, 1985; Verbeek, 2008) and construct panel data at the cohort level from the repeated cross sections. We then use the estimated coefficients from a wage regression in this synthetic panel to construct wage components arising from observable *individual* and *job* characteristics plus an *employer* component in the cross-sectional data itself. Using this decomposition, we document how important each component is for wage growth and wage dispersion over the life cycle. We decompose job characteristics further into a vertical (job level) and a horizontal (occupational) component and find the latter, the pure horizontal component of occupations, to be of negligible importance.

We report corroborating evidence for the importance of job levels from two other data sources, the NCS for the United States and the BIBB/BAuA Employment Survey for Germany. The BIBB/BAuA Employment Survey reports salaries and detailed job characteristics regarding tasks and duties and minimum skill requirements. From these data, we construct job levels using eight survey questions on the responsibility, complexity, and

[1] Although this has high explanatory power, it is not exceptional and is also found for other administrative linked employer-employee data (see, for example, Strub et al., 2008).

autonomy of a job's tasks and duties but no information on workers or employers. The job leveling factors from these questions account for more than 40% of wage dispersion. Using the U.S. NCS data, we provide evidence that our findings extend beyond the German case. We discuss evidence from Pierce (1999) that job characteristics account for 75% of cross-sectional wage variation in the NCS data, and even within occupations, job levels account for half of the observed wage differences. We provide additional evidence that few encoded job levels have high explanatory power across and within occupations also in the NCS data. Finally, we complement the cross-sectional analysis with panel evidence from the German SOEP data where we observe a proxy for job levels. We document life cycle profiles of career ladder promotion and demotion rates and explore how labor market mobility across employers and through nonemployment is related to steps up and down the career ladder.

Our results suggest that the distribution of jobs with certain responsibilities, complexity, and autonomy is key in shaping the macroeconomic wage distribution over time. Changes in the organizational structure of firms create an important demand-side component in wage dynamics and inequality. In this sense, our main findings align well with the established results of Katz and Murphy (1992) and Acemoglu and Autor (2011), who show that wage inequality between education groups is driven by changes in labor demand over time. At the same time, one can expect that the organizational structure of the production process reflects the composition of skills in the workforce, available technologies, and labor market institutions. Consequently, our results suggest that demand across industries, driven not only by technologies and tastes but also by broader institutions, can shape the gross wage life cycle dynamics in the macroeconomy. In that light, our results might help to rationalize the estimated differences in wage dynamics among otherwise technologically similar economies (see, e.g., Krueger et al., 2010; Pham-Dao, 2019). Our findings scrutinize the prevalent assumption in labor market search models that jobs are drawn from a fixed distribution of job types without any rivalry in the availability of jobs other than the congestion externality in search itself. These jobs are gone when the match dissolves. Our results suggest that jobs persist even after worker separation and that rivalry in jobs is important. Rivalry in jobs suggests a new motive for labor market mobility across employers: search for career opportunities. If career opportunities deteriorate with the current employer because of recent promotions of coworkers, other employers might still offer opportunities at the current stage of a worker's career. Labor market search becomes targeted toward career prospects rather than contemporaneous high pay.

The remainder of this paper is organized as follows: Next, we put our results into perspective by reviewing the related literature. Section 2 then introduces the data, and

Section 3 reports the decomposition results. Section 4 provides independent evidence on the importance of job characteristics for the United States and Germany. Section 5 discusses the determinants of career progression. Section 6 explores the role of employer differences when ignoring organizational structure. Section 7 provides conclusions and discusses implications for other strands of economic research. An appendix follows.

1.1 Related literature

Our paper relates to three different strands of existing literature. By exploring the sources of life cycle wage growth and inequality, we relate to the long-standing economic research agenda on determinants of wage differences going back at least to the seminal work of Mincer (1974). His work has developed into a large literature that documented a variety of life cycle wage growth and inequality patterns (for example, Deaton and Paxson, 1994; Storesletten et al., 2004; Heathcote et al., 2005; Huggett et al., 2006). A common practice today is to interpret the residuals from Mincerian wage regressions as wage risk, and a large body of literature is devoted to estimating stochastic processes for these residuals (Lillard and Willis, 1978; MaCurdy, 1982; Carroll and Samwick, 1997; Meghir and Pistaferri, 2004; Guvenen, 2009). Recently, Huggett et al. (2011) and Guvenen and Smith (2014) took more structural approaches to explore the drivers of life cycle inequality. While existing research attributes rising life cycle inequality mainly to residual wage shocks, we add to this literature by relating diverging wages to observable steps on the career ladder and differences between employers. The latter relates our work to Low et al. (2010) and Hornstein et al. (2011) in exploring employer differences as a source of wage inequality in search models, and in particular, to Jung and Kuhn (2016), who explore labor market and earnings dynamics in a life cycle search model.

Our findings are also closely related to the literature on internal labor markets and career dynamics following the seminal work of Doeringer and Piore (1985). The existing research in this strand of literature mostly relies on case studies of single firms and sometimes even subgroups of workers at those firms. Baker et al. (1994) provide one of these fascinating case studies on careers and internal labor markets. They document large wage differences across job levels and show that few job levels—six in their case—suffice to represent the organizational structure of a firm. They find further that, absent promotions across job levels, there is virtually no individual wage growth. Dohmen et al. (2004) provide a case study on the aircraft manufacturer Fokker that corroborates the key findings from Baker et al. (1994) that are relevant for our analysis. Gibbs et al. (2003) and Fox (2009) both document for Swedish matched employer-employee data that promotions along the career ladder are a key source or even the most important source of earnings growth. Regarding differences in career ladder dynamics for males and females, Bronson and Thoursie (2018) document facts from Swedish panel data in line with our findings. They do not, however, observe job levels and resort to coding promotions as large wage changes. In summary, this strand of literature unanimously echos the key idea formulated in Doeringer and Piore (1985, p. 77) that "[i]n many jobs in the economy, wages are not attached to workers, but to jobs."

We complement this strand of research in three dimensions: First, we focus on the life cycle; second, we explore data that are representative of the macroeconomy; third, we relate job levels directly to the underlying characteristics of a job's tasks and duties. By exploring data at the level of the macroeconomy, we overcome a key limitation of existing studies that only observe workers and careers at a single employer. Our empirical results on underlying job characteristics, the differences between job levels and occupations, and the links between labor market mobility and career dynamics further add to the literature.

Waldman et al. (2012) provide an excellent overview on theoretical models of career dynamics. The seminal papers are Lazear and Rosen (1981) explaining promotion dynamics as a result of tournaments and Waldman (1984) emphasizing the signaling role of promotions in an environment with asymmetric information about worker ability. Lazear and Rosen (1981) provide a theory as to why rank-order wage schemes exist in firms; that is, wage schemes where wages do not depend on a worker's output but on the worker's vertical job rank. While the model in Waldman (1984) shares the feature of a rank-order wage scheme, it emphasizes potential inefficiencies from promotion dynamics under asymmetric information. The organizational structure of firms is the focus of the model in Caicedo et al. (2018), who study secular trends in the wage structure. They explicitly incorporate vertical job differentiation into the production process and account quantitatively for changes in wage inequality over time by endogenously changing the organizational structures of firms. Closely related to that work is the paper by Caliendo et al. (2015), who study a sample of French manufacturing firms. They find that four job levels account for up to 66% of within-firm wage variation and provide empirical support for the theoretical model in Garicano and Rossi-Hansberg (2006). Pastorino (2019) proposes a model of employer learning about work ability that also emphasizes the importance of internal labor markets for wage dynamics.

Employer differences as the source of wage differences feature prominently in the strand of the literature that investigates secular trends in wage inequality. Card et al. (2013) provide a particularly relevant example as they study German social security data for the period from 1985 to 2009. Relying on the estimation approach from Abowd et al. (1999), they find that rising between-firm pay differences are an important contributor to rising wage inequality. Song et al. (2015) construct a new dataset from social security data in the United States for the period from 1980 to 2015. Again applying the approach by Abowd et al. (1999), they find that between-firm differences are an important contributor to rising earnings inequality over time. Song et al. (2015) and Card et al. (2013) both argue that changes in the organizational structure of firms are the likely driver of rising between-firm pay differentials. A strand of the literature on secular changes in the wage structure assigns a key role to the interaction of technological change and the task content of jobs. Acemoglu and Autor (2011) provide an excellent survey of this literature. The key idea is that technological change is biased toward certain skill groups or job tasks. This strand of the literature relies on occupations to measure differences across jobs (Autor et al., 2003, 2006). We document a correlation between horizontally differentiated occupations and vertically differentiated job levels, but we also emphasize that occupational wage differences largely disappear when controlling for job-level differences. Our results therefore relate to this literature by suggesting a shift in focus toward vertical job differentiation regarding the responsibility, complexity, and autonomy associated with a job's tasks and duties.

2 The Structure of Earnings Survey data

We use data from the 2006, 2010, and 2014 waves of the Structure of Earnings Survey ("Verdienststrukturerhebung"), henceforth SES, for the main part of our analysis. The SES data are an administrative representative survey of establishments (i.e., plants). The survey is conducted by the German Statistical Office, and establishments are legally obliged to participate in the survey so that selection due to nonresponse does not arise. The data are employer-employee linked and contain establishment-level and employee-level information. Establishments with 10 to 49 employees have to report data on all employees. Establishments with 50 or more employees report data only for a representative random sample of employees. Small establishments with fewer than 10 employees are not covered by the data (prior to 2014). Data on regular earnings, overtime pay, bonuses, and hours paid, both regular and overtime, are extracted from the payroll accounting and personnel master data of establishments and transmitted via a software interface to the statistical office.[2] Transmission error is therefore negligible.

The data cover public and private employers in the manufacturing and service sectors. Self-employed workers are not covered. The survey has information on about 3.2 million

[2] The German Statistical Office offers an interface to directly transfer survey data. This is currently used by about 20% of firms. Most firms use software modules by commercial software providers to extract and transfer the data. See Statistisches Bundesamt (2016) for further details.

employees from roughly 28,700 establishments in 2006, 1.9 million employees from 32,200 establishments in 2010, and 0.9 million employees from 35,800 plants in 2014. The number of sampled employees decreased over time because the sampling probability of plants became smaller to reduce bureaucratic costs.

2.1 Sample selection and variable definition

For our baseline analysis, we restrict the data to workers ages 25 to 55. We drop very few observations where earnings are censored[3] and all observations for which the state has a major influence on the plant.[4] We drop observations from the public administration and mining industry and observations with missing occupation or job-level information. We use plant fixed effects in our analysis and therefore drop all observations where our sample selection by age leaves us with fewer than 10 workers at a plant. The baseline sample has 2.39 million observations. Our wage measure is monthly gross earnings including overtime pay and bonuses divided by regular paid hours and paid overtime hours. In our regression analysis, we use controls for experience, education, sex, occupation, and job level. We construct experience as potential experience starting at age 25. Sex is naturally coded. For education, we consider four groups: workers with only secondary education, workers with secondary education and additional vocational training, and workers with a college education. The fourth group are workers for whom education is not reported or who have other levels of education. Importantly, this group includes workers who have not completed a secondary education. For convenience, we will refer to the education level of this fourth group as *other* for the remainder of the analysis.[5] For occupation coding, we use two-digit 2008 ISCO codes. We rely on a crosswalk provided by the International Labour Organization (ILO) together with additional occupation codes from the German employment agency (KldB 1988) to recode occupations in the 2006 data.[6] We next describe the job-level variable in detail.

[3]The censoring limit is 1,000,000 € in 2006 and 750,000 € since 2010 in annual gross earnings. We impose the latter throughout.

[4]We run a robustness check where we include publicly owned/dominated plants, too; see Appendix B. For a large set of observations, the information on public ownership is missing. The information is available only if in a region-industry cell there are at least three firms in which the state has a major influence. Major influence is defined as being a government agency, the state owning $\geq$ 50% share, or influence arising from other regulations.

[5]The 2014 data provide an additional education variable with slightly more detailed information than the education variable we use because it is available in all other datasets. It shows that all workers without a completed secondary education are coded in our education variable as the "other" group.

[6]Crosswalk retrieved from International Labour Organization, ISCO—International Classification of Occupations "ISCO-08 Structure, Index Correspondence with ISCO-88," http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm.

2.2 Job responsibility, complexity, and autonomy: job levels

Importantly and different from many other data sources, our data distinguish among five job levels in describing jobs of workers. These job levels are defined based on a job's complexity (skill and typical educational requirements), responsibility (for one's own work or the work of others), and autonomy (the decision-making power and discretion in the work flow) derived from the tasks and duties of a job.[7] The statistical office provides descriptions for job levels 1 to 5 but does not assign titles. To ease the discussion, we assign labels to the job levels. The lowest job level is assigned to simple tasks with clearly defined duties. These jobs have no minimum skill requirements so that they can be done by untrained workers (*untrained, UT*). Specifically, the minimum skill requirements are set so that tasks do not require particular training (such as an apprenticeship) and can be learned on the job in less than three months. The second job level covers tasks that require some occupational experience but no completed occupational training such as an apprenticeship (*trained, TR*). Tasks performed at this job level can be typically learned on the job in less than two years. Duties on the lowest two job levels are clearly defined so that workers do not undertake any decisions independently and follow a clearly defined work flow. Importantly, skill requirements are defined independently of the worker who does the job and define the minimum skills required to complete tasks and duties defined by the job. Only from the third job level onward do employees have some discretion regarding their work flow. Jobs at the third job level (*assistants, AS*) typically require a completed occupational training (apprenticeship) and, in addition, occupational experience. At this job level, jobholders prepare decisions or make decisions within narrowly defined parameters. Examples would be tradespeople, junior clerks, or salespeople who decide on everyday business transactions (e.g., sales) and thus have some discretion about work flow. Yet, the duties of these jobs do not include responsibility for the work of others or strategic business decisions. The fourth job level is assigned to jobs with tasks and duties that typically require both specialized (academic or occupational) training and experience (*professionals, PR*). Importantly, these jobs require that tasks are performed independently and are associated with substantial decision-making power over cases, transactions, or work flow organization. The complex tasks assigned to these jobs typically require autonomy in organizing work flow to successfully complete the job tasks. Jobholders of professional jobs have some decision-making power in regard to the work of others; typically, they oversee small teams (examples would be production supervisors, junior lawyers, or heads of administration offices). The fifth job level is managers and supervisors (*management, MA*). The tasks and duties of these jobs are primarily decision

[7] We discuss similarities to modern occupational codes in Appendix A.2.

making and dealing with complex cases that require high levels of autonomy and often come with substantial responsibility regarding the work of others (examples are senior lawyers, medical doctors, and senior researchers). In Section 4, we use survey questions on requirements, tasks, and duties to construct job levels and explore their explanatory power for wages, and we discuss the similarity to job levels in the U.S. NCS data.

Importantly, job levels are derived from job requirements rather than from the skills or completed education of the jobholder. As described above, education can be a minimum skill requirement and hence a necessary condition. Yet, education is not sufficient to work at a high job level. College graduates can work in untrained jobs as well as in management jobs. As we will see, what accounts for wage differences across workers are different jobs rather than differences in workers' completed education. This also implies that job levels are neither an educational nor occupational concept, but both are correlated to the job level. In Appendix A, we document that each education group is represented significantly in at least three job levels, and the typical occupation in our sample spans three job levels. Appendix A also provides further detailed information on the definition of the job level variable. As discussed in Section 1.1 above, job levels reflect the organizational structure of the production process within a plant and are independent of the wage structure, as has been shown in existing case studies (Dohmen et al., 2004).

2.3 Descriptive analysis

Table 1 reports the number of observations for each SES wave as well as information on average wages and wage inequality for our baseline sample. We report real wages in constant 2010 prices using the German CPI deflator. The average real hourly wage is roughly € 20 (€ 16) for men (women) and has not grown much since 2006. Median real wages have been falling from roughly € 18.0 in 2006 to € 17.6 in 2010 for males but returned to € 18.4 in 2014. Female median real wages have fallen from € 14.7 to € 14.4 between 2006 and 2010 and then grew again to € 14.9 in 2014. This means that female wages are roughly 20% lower than male wages on average. Wage inequality increased somewhat for both genders between 2006 and 2014 and is higher among men. The p90/p10 ratio went up from 3.1 to 3.3 for males and from 2.7 to 3.0 for females. Gini coefficients also show a slight increase over these nine years, from 0.26 to 0.27 for males and from 0.22 to 0.24 for females.

The right panel of Table 1 reports the population shares of workers on the five job levels. The share of male (female) workers in jobs with high or very high autonomy in decision making (MA+PR) increased from 33.8% (22.4%) to 35.0% (23.9%) over the three waves. The share of male (female) workers in jobs with some autonomy (AS) has increased from

Table 1: Summary statistics for wages and hierarchies in the SES, 2006-2014

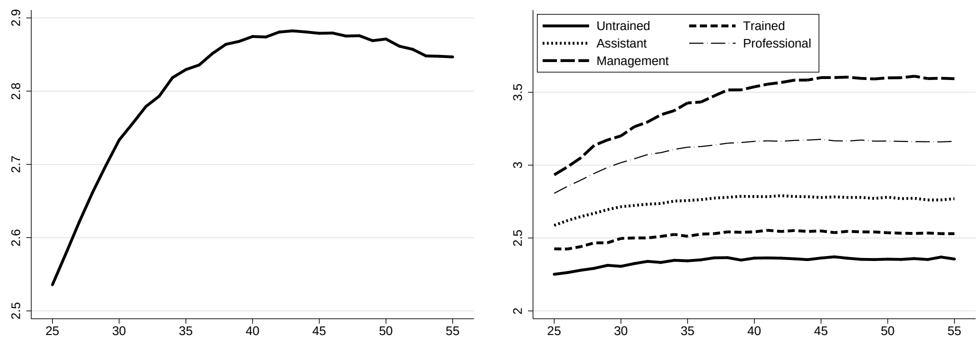
	Wages (in 2010 €)					Pop. Share of Job Level (in %)					
	Av.	Gini	p10	p50	p90	UT	TR	AS	PR	MA	N. Obs
Males											
2006	20.5	0.26	10.5	18.0	32.8	5.8	17.0	43.4	24.3	9.5	706,886
2010	20.3	0.28	9.9	17.6	33.3	7.7	17.2	41.5	22.4	11.1	581,442
2014	21.3	0.27	10.4	18.4	34.8	5.6	13.5	45.9	23.6	11.4	187,568
Females											
2006	15.9	0.22	8.7	14.7	23.8	12.5	18.9	46.2	18.5	3.9	431,016
2010	15.8	0.24	8.4	14.4	24.2	13.9	17.5	45.6	18.2	4.8	353,863
2014	16.6	0.24	8.7	14.9	25.9	9.6	15.1	51.4	18.2	5.7	125,185

Notes: "Wages" refers to the hourly wages in constant 2010 prices. "Av." is the average and "p10/50/90" are the 10/50/90 percentile of the wage distribution, respectively. "Pop. Share of Job Level" refers to the population share of a job level in the sample population, where "UT/TR/AS/PR/MA" are untrained, trained, assistants, professionals, and managers, respectively. "N. Obs." refers to the unweighted number of observations in the baseline sample.

43.4% (46.2%) to 45.9% (51.4%), while the share of male (female) workers in jobs that have no autonomy (TR+UT) went down from 22.8% (31.4%) to 19.1% (24.7%).

Figure 1(a) shows that the average wage of an employee increases substantially during the working life. The cross-sectional average of workers' wages increases by roughly 2% with every year of age between age 25 and age 45 and levels off afterward. Yet, this average wage increase masks substantial heterogeneity. Figure 1(b) reports the mean log wage by age conditioning on job levels. We find that wages in the top job level (MA) are always the highest and that the average wage at this job level sees the strongest increase by age, so that the wage differences between the top level and the other groups widen with age. For example, the average wage of a job at the *assistant* level increases by less than 20 log points (22%) over the working life, roughly half the average wage increase, whereas at the management level, wages rise by more than 60 log points (82%), roughly twice the average increase. The difference between the average wage of a 25-year-old in an untrained job and a 55-year-old in a management-level job is a stellar 140 log points (306%). These descriptive statistics suggest that moving up the career ladder is an important contributor to life cycle wage growth. Other potential contributors to wage growth could be occupational mobility, mobility toward better-paying plants, further formal education, or pure returns to experience. The next section decomposes wage

Figure 1: Wage by age and job level



(a) All workers (b) Wages by job level

Notes: The left panel shows the average (log) real wage by age over all workers and sample years. The right panel shows mean (log) real wage by age and job level. Year fixed effects have been removed.

growth over the life cycle into the contribution of each of these components.

For our decomposition analysis, it is key that the SES data are exceptional in that the job, worker, and plant characteristics account for more than 80% of wage variation in the cross section if we use plant fixed effects. Even without plant fixed effects but with plant-level controls, we account for 62% of wage variation in the cross section; see Table 8 in Appendix A. Part of this high explanatory power is owing to the high quality of the data. A second part comes from the fact that the data contain information about job levels. Using only job-level dummies accounts for over 45% of the cross-sectional wage variation in our sample.

3 The life cycle of wage growth and wage inequality

This section explores how much plant, job, and worker characteristics account for life cycle wage growth and the rise in wage inequality over the life cycle. One concern with such a decomposition is that unobserved individual characteristics jointly affect wages and the career progression of workers. We deal with the challenge of unobserved heterogeneity by using synthetic panel methods. A simple OLS estimate of, for example, wages on job levels might be inflated because more able workers obtain higher wages at any job and are also more likely to end up in higher job levels. The synthetic panel method exploits the fact that aggregation of the microdata to the level of a cohort creates a panel structure so that we can control for unobserved heterogeneity in the decomposition (see Deaton, 1985; Verbeek, 2008, for an overview of the method).[8]

[8]Appendix B.2 considers a specification where we do not control for individual fixed effects.

3.1 Methodology

To be specific, assume that log wages w_{ipt} of individual i working at plant p at time t are given by

$$w_{ipt} = \gamma_i + \zeta_{pt} + \beta_J J_{ipt} + \beta_I I_{ipt} + \epsilon_{ipt} \tag{1}$$

where J_{ipt} is the characteristics of the job of individual i at plant p at time t, I_{ipt} is the characteristics of the individual itself, γ_i is a worker fixed effect, and ζ_{pt} is a plant-year effect. The *individual component*, $\beta_I I_{ipt}$, captures the wage effect of worker characteristics in our analysis of education and gender-specific age dummies.[9] The *job component*, $\beta_J J_{ipt}$, captures the characteristics of a job. We use dummies for two-digit occupations and five job-level dummies. To control for plant-year effects, we demean all variables at the plant level (year by year):

$$\hat{w}_{it} := w_{ipt} - w_{.pt} = \hat{\gamma}_i + \beta_J \hat{J}_{it} + \beta_I \hat{I}_{it} + \hat{\epsilon}_{it}, \tag{2}$$

where $\hat{X}_{it}$ denotes the difference between variable X_{ipt} for worker i and its average $X_{.pt}$ at the plant where this worker is working. To construct an estimate of the plant component, ζ_{pt}, we need estimates for the coefficients β_J and β_I. To control for individual-specific fixed effects, when estimating these coefficients, we rely on panel regressions for synthetic cohorts. We define cohorts based on workers' sex, birth year, and regional information (north-south-east-west)[10], and we aggregate variables to the cohort level to obtain

$$\hat{\hat{w}}_{ct} = \hat{\hat{\gamma}}_c + \beta_J \hat{\hat{J}}_{ct} + \beta_I \hat{\hat{I}}_{ct} + \hat{\hat{\epsilon}}_{ct}, \tag{3}$$

where $\hat{\hat{X}}_{ct}$ denotes the average of $\hat{X}_{it}$ within cohort c. We use fixed effects OLS to obtain estimates $\tilde{\beta}_J$ and $\tilde{\beta}_I$ from equation (3). Using the coefficient estimates $\tilde{\beta}_J$ and $\tilde{\beta}_I$, we constructed the estimate for the plant component $\tilde{\zeta}_{pt}$. The plant component represents the residual plant-level wage after accounting for worker and job observables. It is given by

$$\tilde{\zeta}_{pt} = w_{.pt} - \tilde{\beta}_J J_{.pt} - \tilde{\beta}_I I_{.pt}. \tag{4}$$

This means that the plant component corrects the average wage at a plant for differences in organizational structure and workforce composition by removing the average individual

[9] We group ages using three-year windows to identify cohort effects later on, given the four-year distance between the three survey waves.

[10] The annual gross migration rate between German states in the past 30 years is low and has been roughly 1.3% per year; see *Wanderungsstatistik* of the Statistisches Bundesamt. More than a third of this migration is between states of the same region.

and job components across plants. A high-wage plant is a plant that pays on average more than other plants after accounting for worker and job observables at that plant.

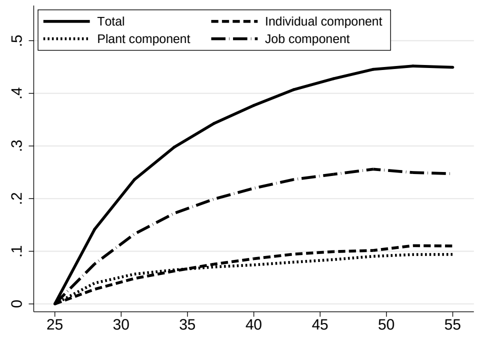
The minimum observations across cohort-year cells is 415, the maximum is 8,383, and the median is 3,461. The identifying assumptions for our regression are that all coefficients, in particular the pure experience effects on life cycles (captured by β_I), are stable across cohorts and that regressors have overlapping support across cohorts.

To understand the identifying variation that we exploit, recall that we have first demeaned the data at the plant-year level and hence have implicitly taken out region-year effects as well, and second, we have taken out cohort effects in the estimation. Therefore, we do not use differences across cohorts or common time trends of all cohorts in a region for identification, but instead exploit different time variation across cohorts for identifying β_J and β_I. In other words, we exploit how wages and (job) characteristics evolve over time within a cohort; while simultaneously controlling for variations that affect all cohorts in that region.

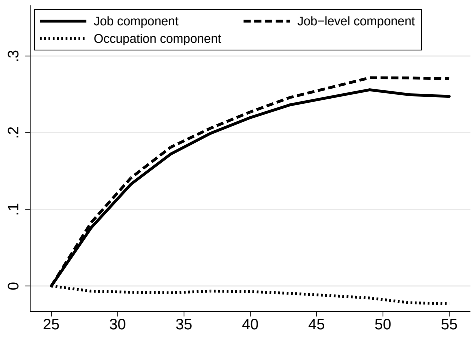
An example for the type of variation that we use is, say, the entry of a new plant into a region, for which this plant has an atypical organizational structure. This should have more of an effect on the job characteristics of worker cohorts that are young at the time of entry at that plant relative to those of older cohorts. Moreover, the effect should be strongest around the entry date at that plant because younger workers are more mobile and hence more likely to exploit new job opportunities. Another example would be (regional) business cycles with heterogeneous impacts on cohorts. More generally speaking, identification comes from changes in the structure of job opportunities within a region over time, but since this affects different age groups differently, the variation is not captured by the region-year effect.

However, for the plant component we estimate, identification is weaker because it is not based on observing workers that switch plants, as in Abowd et al. (1999). In turn, our estimate for the plant component will also capture the average *unobserved* heterogeneity of workers within a plant. We cannot identify the average unobserved worker type at a plant or the plant type itself. Consequently, the estimators for the various components are consistent if there is no assortative matching in unobserved plant and worker heterogeneity. If matching is positively (negatively) assortative, the plant effect tends to be positively (negatively) biased.

Figure 2: Wage and job component decomposition (males)



(a) Wage



(b) Job component

Notes: Left panel: Decomposition of log wage differences by age relative to age 25 for male workers. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. The horizontal axis shows age, and the vertical axis shows the log wage difference. Right panel: Decomposition of the job component (solid line) into the contribution of occupations (dotted) and job levels (dashed).

3.2 Wage growth

Using the estimated individual, job, and plant components, we decompose mean log wages over the life cycle. We construct for each worker the predicted wage and the worker, plant, and job components. Note that the estimated components $\tilde{\beta}_I I_{ipt}$ and $\tilde{\beta}_J J_{ipt}$ use worker and job characteristics that can still contain cohort effects. Therefore, we remove these effects from the estimated components by regressing wages on a full set of cohort and age dummies. We report the coefficients on the age dummies as our life cycle profiles and always normalize the log wage of a 25-year-old to zero. We decompose the wage growth of male and female workers separately because these decompositions show very distinct patterns for males and females. We first look at males, discuss female workers in the second step, and compare decompositions in a third step.

3.2.1 Males

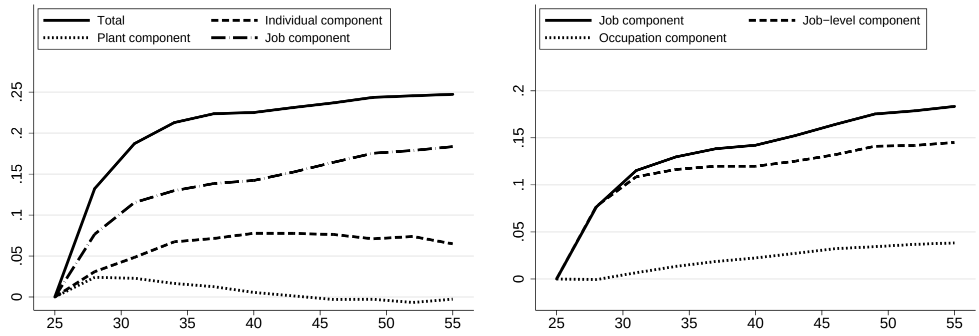
Figure 2(a) reports the decomposition of mean log wages for men. On average, wages grow by approximately 45 log points over the life cycle.[11] The job component, climbing the career ladder, accounts for more than 50% and up to 58% of wage growth. Moving to better-paying plants over the life cycle contributes approximately 20% to wage growth. The remainder, the individual component, captures a pure experience effect.

[11] The difference relative to Figure 1 stems from cohort effects; that is, younger cohorts enter at higher wages.

Within the job component, it is promotions across job levels that account for average wage growth, as Figure 2(b) shows. In fact, movements across occupations contribute slightly negatively to wage growth, controlling for job levels. In turn, most of the life cycle wage growth is accounted for by workers taking on jobs at higher job levels, meaning jobs with increasing degrees of responsibility, complexity, and autonomy over the course of their careers.

3.2.2 Females

Figure 3: Decomposition of wage and job component (females)



(a) Wage (b) Job component

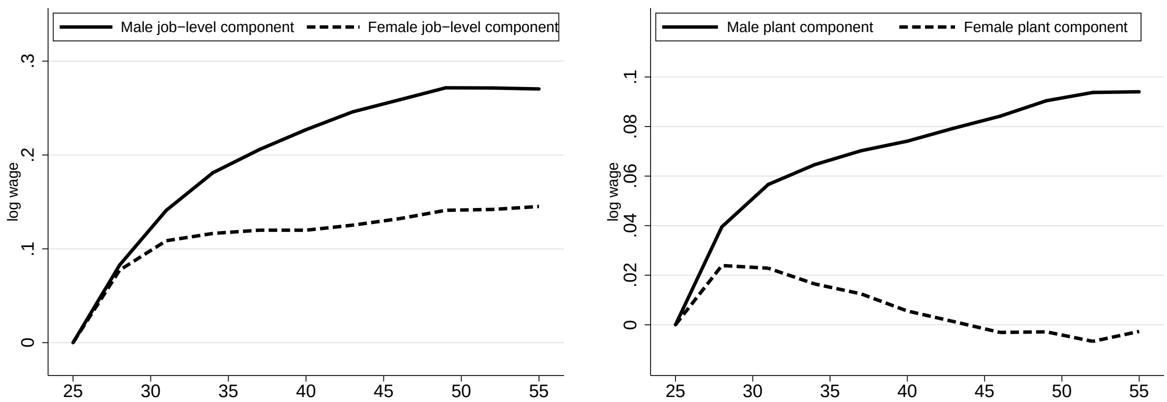
Notes: Decomposition of average wages of female workers; otherwise, see Figure 2.

The average wages of females are lower and grow less over the life cycle relative to male wages. Our decomposition in Figure 3(a) shows that a substantial part of this difference is accounted for by the smaller increase in the job component, in particular, a slower progression of women on the career ladder. Female wages grow by only 25 log points compared to 45 log points for males. The job component still accounts for the lion's share (18 log points), but compared to males (25 log points), the average female job component is substantially flatter. The reason is that between age 30 and age 45, there is hardly any growth in the job component for females. It starts to increase slightly again only after age 45. Unlike for men, we find for women that a substantial part of the increase in the job component stems from the occupation component, which accounts for almost 5 log points of females' wage growth (Figure 3(b)). The individual component for females accounts in relative terms for slightly more of the total growth than for men (30% versus 25%). Interestingly, the plant component shows a decreasing profile for females after age 30. One reason could be that the nonwage aspects of a plant, such as its location or working time arrangements, play more important roles for females than for males at this stage of the life cycle. As we document below, the plant component is correlated with the organizational structure of plants. Plants with a high plant component offer on average more jobs at top job levels. The decomposition shows that, over time, fewer and fewer females work at these plants.

3.2.3 Comparing male and female careers

One result of these different career paths is that males and females earn significantly different wages in the German labor market. At labor market entry (age 25), females in our sample receive a roughly 7% lower hourly wage than males. As a raw average, this difference may still contain occupational and employer differences. At the age of 50, females earn wages that are more than 30% lower than wages for males. Figure 4(a) highlights how much the career ladder, differences in job levels, accounts for the widening of the gender wage gap over the life cycle. It shows the estimated job-level component from Figure 2 (males) and Figure 3 (females).

Figure 4: Job-level and plant components of males and females



(a) Job-level component

(b) Plant component

Notes: (a) Job-level component from decomposition of mean log wages for males and females. (b) Plant component from decomposition of mean log wages for males and females. Both: Horizontal axis shows age, and vertical axis shows log wage difference.

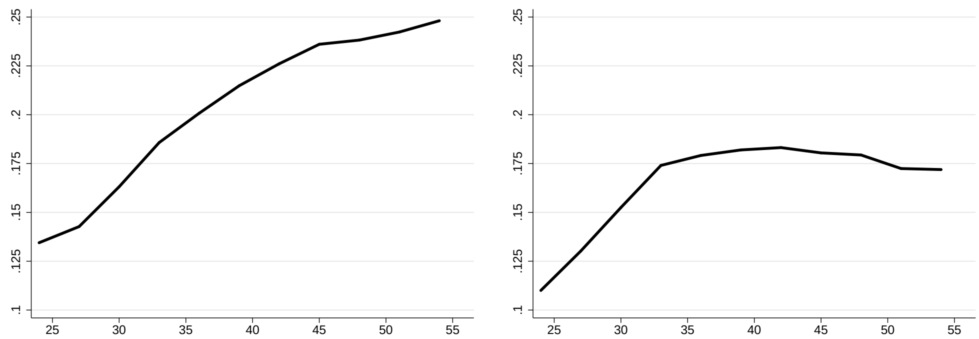
Up to age 30, males and females experience a virtually identical increase in the job-level component. After age 30, the career progression of females comes to a halt, while males keep on climbing the career ladder for an additional 15 to 20 years. This results in an increasing wage difference between males and females exceeding 10 log points at the age of 50, thereby accounting for almost half of the increase in the gender wage gap over the life cycle. Close to all of the remaining 10 log points of the differential wage growth is accounted for by differences in mobility across plants. While males move on average to plants that pay better, females after the age of 30 tend to move to plants that pay worse; see Figure 4(b).

The caveat with this analysis is that our sample spans only 9 years, and the estimated life cycle pattern also comes from comparisons across cohorts. Interpreting these results as life cycle facts and extrapolating them to the expected life cycle profiles for younger cohorts of women should therefore be done with this caveat in mind. In Section 5.3, however, we provide additional evidence that supports the view that career dynamics differ between males and females from SOEP panel data that spans more than 30 years.

3.3 Wage inequality

While average wages grow, wage dispersion also increases over the life cycle. The high degree of statistical determination in our data allows us to provide a fine-grained decomposition of the drivers of this rising wage inequality over the life cycle. Figure 5 shows the variance of log wages for males and females by age from the raw data. We find the typical pattern of an almost linear increase in the cross-sectional variance for males. For females, the pattern is similar until their early 30s and flat thereafter. We rely on regression results from above to decompose the life cycle increase in wage inequality in this section. We construct variance and covariance estimates of the job, individual, and plant component by age to decompose the life cycle increase in wage dispersion. As for wage growth, we first discuss males, then females.

Figure 5: Variance of log wages by age (raw data)



(a) males (b) females

Notes: Variance of log wages for males and females. Left panel shows males, right panel shows females. Horizontal axis shows age, and vertical axis log wage variance.

3.3.1 Males

The variance of log wages for men increases substantially over the life cycle: 11 log points over 30 years (15 log points after controlling for cohort effects). Bayer and Juessen (2012) find a comparable number for average household wages in the German SOEP data. Heathcote et al. (2010) report for the United States an increase between 17 and 20 log points over the same part of the working life. Existing microdata based on cross-sectional regressions account for about 30% of the wage inequality by observables and leave the largest part of wage inequality unexplained. Consequently, the literature interprets the largest part of the increase in wage inequality by age as the result of idiosyncratic risk captured by a stochastic process. This is the typical approach in a wide range of models including the large class of microfounded models of consumption-savings behavior.

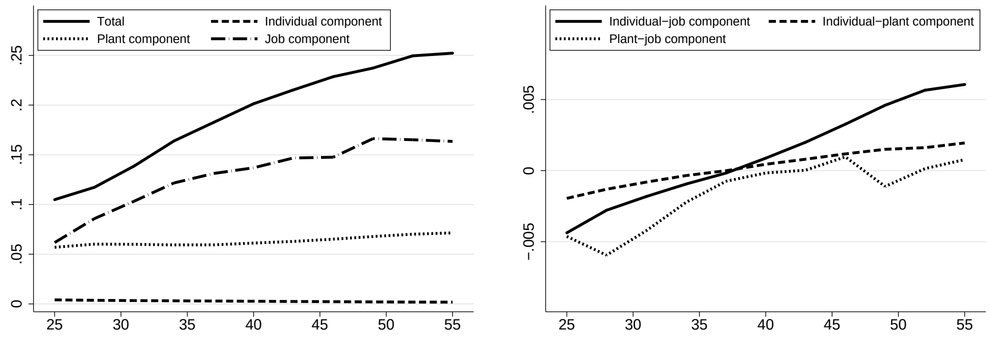
In Figure 6(a), we display the decomposition of life cycle wage dispersion.[12] We find that the variance of log wages of workers increases from roughly 10 log points to 25 log points. The variance of the plant component contributes to the level of wage dispersion with 6 to 7 log points. The job component, by contrast, shows an 11 log point increase in its variance, from 6 to 17 log points. In words, two-thirds of the total increase in wage variance is accounted for by workers becoming increasingly different in the type of jobs they hold. As for average wages, the job level is the main driving variable (not displayed). The variance of the individual component is virtually zero. Education itself has a negligible direct effect on wage differences across workers. Yet, as we will show in Section 5, it has a strong indirect effect through promoting a worker's career.

There are two remaining components unreported in Figure 6(a): the variance of what is not accounted for by observables (residual wage dispersion) and the sum of all covariance terms of observables. Figure 6(b) shows the covariance terms by splitting the covariance into components due to covariances between the job, individual, and plant components by age. We find that the covariance terms are on average close to zero. Yet, they show a systematic life cycle pattern. In particular, the covariances between the individual (education) and the job components and between the plant and job components increase over the life cycle. This means that young workers who are at high job levels tend to be at low-paying plants and tend to have lower levels of education. When workers age, workers at high job levels are found in all plants and are most likely to have high degrees of formal education.

The sum over the two covariance terms that involve the job component increases from slightly less than -1 log point to slightly less than +1 log point over the life cycle. This

[12] Here, we control for cohort effects and the profile becomes steeper relative to the raw data in Figure 5.

Figure 6: Variance-covariance decomposition (males)



(a) Variance

(b) Covariance

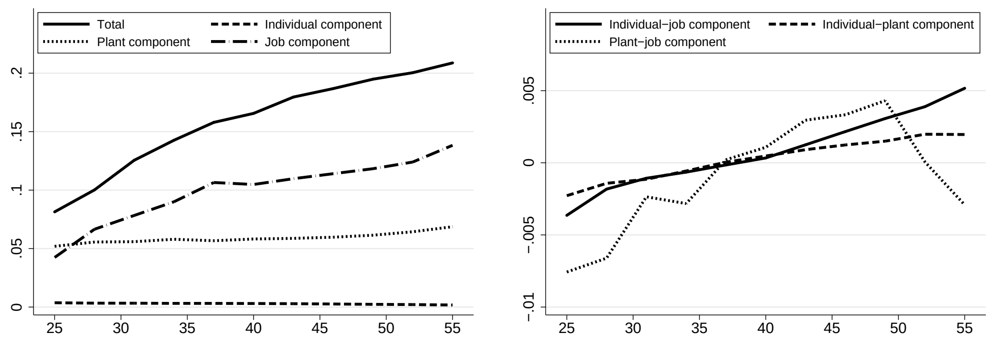
Notes: Left panel: Decomposition of the variance of log wages by age for male workers. Variances of all components are calculated by age-cohort cell. The solid line is variance of total wage, dashed line the individual, dotted line the plant, and dash-dotted line the job component. Right panel: Covariance components for variance decomposition calculated analogously to the left panel; the solid line refers to the covariance of the individual and job component, the dashed line to the covariance of the individual and plant component, and the dotted line to the covariance of the plant and job component; all covariances are within the age-cohort cell.

means that the covariance terms contribute another 4 log points to the increase of the variance over the life cycle (twice the difference between the two covariance terms). This accounts for a large part of the wage dispersion increase not accounted for by the job component alone. Hence, the dispersion in the job component and the covariance of the job, plant, and individual components account for virtually all of the increase in wage dispersion over the life cycle. As a consequence, residual wage dispersion shows in our decomposition only a small increase over the life cycle (4 log points). We show this in Figure 21 in Appendix B.3. In summary, the rising wage differences over the life cycle are typically attributed to persistent shocks to residual wages when data do not contain job-level information, but we attribute these differences mostly to (persistent) observable differences in career progression.

3.3.2 Females

We have seen that women have a flatter job-level component than men after age 30. This result also has implications for the evolution of life cycle wage inequality among women. Their wage dispersion grows less in age; see Figure 7(a). In particular, the increase accounted for by job-level dispersion is much smaller in age for women than for men and levels off after age 30. Still, the life cycle profile in the job component accounts for over 2/3 of the 12 log point increase in wage dispersion over the working life of females (compared to a 15 log point increase in the variance for males). For females, we also find a virtually flat life cycle profile in the plant component (Figure 7(a)) and residual component (Figure 21 in Appendix B.3). At the same time, the job-plant covariance profile is even steeper for women than for men (Figure 7(b)). Those women who end up at high job levels at age 50 work in high-paying plants. Yet, from Figure 4 we know that later in their working life, fewer women tend to work in high-paying plants than they do at the age of 30.

Figure 7: Variance-covariance decomposition (females)



(a) Variance (b) Covariance

Notes: Decomposition of the variance of wages of female workers; otherwise, see Figure 6.

3.4 Robustness and sensitivity

Appendix B provides an extensive robustness analysis. We explore heterogeneity in the importance of jobs for wages across workers covered by collective bargaining, workers working full-time, and workers working in large plants. In summary, we find that the importance of jobs in accounting for wage dynamics increases for workers not covered by collective bargaining and decreases in large plants. Results for wage growth are very similar for full-time male workers, and the effect becomes slightly lower for female workers. For the increase in wage dispersion, we find again that the job component becomes more important for workers not covered by collective bargaining and less important in large plants. The contribution to increasing wage dispersion for full-time workers is slightly lower than in the baseline for both male and female workers. We also explore the sensitivity of our results when we include public employers and publicly controlled firms. When including public employers, we find a 30% larger job component for female wage growth over the life cycle. This suggests that public employers offer more opportunity for female career dynamics, in line with over 60% of employees being female at these employers. Overall, we find that the key findings on the importance of the job component are robust across specifications and sample selections. We relegate further details and discussion to Appendix B.

4 Job characteristics and job leveling

The high explanatory power of the job level for wages might raise concerns regarding reverse causality. The concern might be that, when asked to level a job of a specific, say well-paid, worker, an employer will assign a high job level without that job level actually reflecting the tasks and duties of the job of said worker. To address this concern, we use independent data from the BIBB/BAuA Employment Survey 2012 on job requirements, working conditions, and wages (Hall et al., 2018) to validate our findings from the previous section outside the SES data. In a second step, we consider data from the NCS for the United States to provide further corroborating evidence from outside Germany on the importance of jobs in accounting for cross-sectional wage differences.

4.1 Evidence from BIBB/BAuA

The BIBB/BAuA data on jobs and their characteristics also contain worker demographics and typical labor market data such as occupation, industry, and employer size. For the analysis, we restrict the sample to be in line with our previous analysis. We keep workers ages 25 to 55 who work at employers with at least 10 employees and drop workers in public service. We drop self-employed workers, freelance workers, independent contractors, and family workers. We further restrict the sample to workers who do not report second jobs and who report regular working time between 35 and 45 hours per week to reduce measurement error in hours.[13] Some of the wage information in the survey has been imputed, and we drop all observations with imputed wage information. We further restrict the analysis to white-collar worker but also report results for blue-collar workers in Appendix C.[14] The final sample has 3,027 observations with complete information for the analysis.

The survey collects data from workers on their monthly earnings and typical hours worked. We use these data to construct wages. Constructed wages in the BIBB/BAuA data likely contain substantially more measurement error than wages from the SES data that are based on employer-reported earnings and hours paid. This is important to keep in mind

[13] Appendix B shows that our previous results based on SES data are very similar if we consider full-time workers only.

[14] Information on task complexity is coded separately for blue-collar and white-collar workers that make the data intricate to aggregate and compare.

Table 2: Wage regressions for white-collar workers (Angestellte)

controls	adj. R^2
job-leveling factors	0.441
+ occupations	0.486
+ employer characteristics + region	0.612
occupation + employer	0.517

Notes: Adjusted R^2 from different regressions of log wages on different sets of observables (see text for details). The regression sample always contains 3,027 observations for white-collar workers.

as higher measurement error will reduce the explanatory power of job characteristics for wages in the regression analysis below. To describe job characteristics, we select eight questions from the survey that we identify to be informative about a job's responsibility, complexity, and autonomy and therefore describe relevant job-level information. Broadly, these questions summarize the complexity and required skills for the job, the autonomy in organizing work flow, the degree of communication, and whether the job involves supervisory duties. Importantly, none of the information is on worker characteristics such as workers' highest degree of education or age. We report the detailed survey questions in Appendix C. We encode answers to these questions using dummy variables and refer to these as *job-leveling factors*. In a first step, we explore the explanatory power of the job-leveling factors by running a series of linear wage regressions. Table 2 reports the R^2 from these regressions.

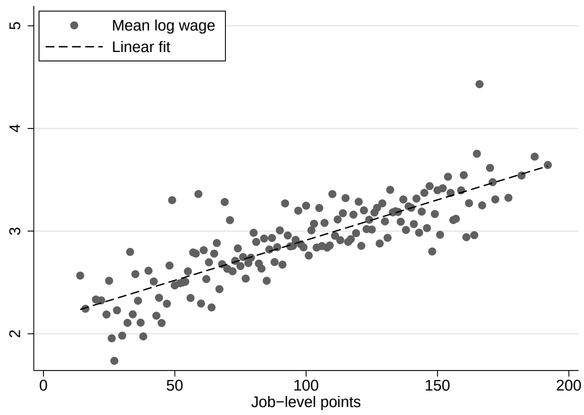
When we run a regression on the job-leveling factors only, we account for 44% of wage variation.[15] This high explanatory power aligns closely with our results for the SES data. In the SES data, job levels alone account for 46% of the overall wage variation. Adding occupation information to the job-leveling factors increases the explanatory power only slightly to 49%. Such a small contribution also aligns with our results from the SES data where occupations account for only a very small fraction of the job component. If we further add employer characteristics, we account for 61% of the wage variation. In the SES data, a regression on plant characteristics and job levels accounts for 62% of the wage variation.

In a second step, we construct job levels based on a job-leveling scheme. Job leveling is a widespread human resource tool to assign wages to jobs based on job-level points that are assigned to specific tasks and duties. Job leveling thereby explicitly assigns a

[15] The regression involves 18 dummies for answers to the eight questions and a constant.

base wage to a job. This base wage can then be further complemented by variable pay components. We apply such a job-leveling scheme based on the answers to the eight survey questions underlying our job-leveling factors. It is important to point out that the BIBB/BAuA survey was never designed to be used in combination with such a job-leveling scheme, so we have to assign point values to questions and answers to these questions. As job-leveling scheme, we rely on the leveling scheme underlying the German steel and metal worker bargaining agreement (*ERA-Punktebewertungsbogen zur Bewertung von Arbeitsaufgaben*). The fact that the survey contains questions that can be mapped onto the components from such an existing job-leveling scheme provides suggestive evidence that these job characteristics are considered relevant in practice. We describe our mapping of survey answers to the job-leveling scheme in Appendix C.1. After assigning each worker observation job-level points depending on the answers to the survey question, we run a simple linear regression of the log wage on the assigned total of job-level points, and this regression accounts for 39% of the wage variation. This is slightly lower than the 44% from the more flexible regression on job-leveling factors in Table 2. Figure 8 shows the relationship between job-level points and the average log wage for each point level. Although there is still substantial dispersion that in part reflects sampling uncertainty, the data show a clear positive relationship between job-level points and average (log) wages. In Appendix C, we report the distribution of wages by point levels and show that for each point level, the dispersion is small.

Figure 8: Average wages by job-level points



Notes: Average (log) wages by job-level points. Job-level points have been constructed from survey questions on job characteristics (see text for details). Each dot represents the average log wage for the job-level points. Dashed line shows linear fit.

Three points are important to emphasize regarding these results. First, the coding of job-level points involves only eight survey questions regarding a job's responsibility, complexity, and autonomy. Second, neither worker nor wage information has been used for assigning points to jobs. Third, the assignment of job-level points is very rough and represents our attempt to map answers to job-level points. Sophisticated data analysis could likely improve the in-sample fit between job-level points and wage data considerably, and obviously a more targeted survey regarding the components of the job-leveling scheme would also allow for a more accurate assignment of job-level points. In Appendix C, we demonstrate however that our job leveling successfully recovers the bargained union wages, except for jobs at very low levels, where there is strong compression in union wages.

4.2 Evidence from the U.S. National Compensation Survey

Besides reverse causality, another concern regarding our results on the importance of job characteristics for wages might be that these results represent a particularity of the German labor market with its institutions and traditions. We therefore discuss next evidence based on the National Compensation Survey (NCS) for the United States. The NCS is a nationally representative employer survey conducted by the Bureau of Labor Statistics (BLS) that collects information from private industry as well as state and local government establishments. The survey collects detailed job characteristics that are aggregated to job levels using the BLS job-leveling system. The BLS job-leveling system evaluates jobs according to their required knowledge, job controls and complexity, contacts (nature and purpose), and physical environment.[16] Importantly, the NCS data do not contain worker-level information but only information about employers and jobs. The BLS provides detailed information that describes the job-leveling procedures in the NCS (see Appendix A.3 for more details).[17]

Pierce (1999) uses microdata from the NCS to explore the explanatory power of different job-leveling factors for wages. Our analysis of BIBB/BAuA data above is inspired by his original work. He runs cross-sectional wage regressions on different combinations of job and establishment attributes and job-leveling factors. Because the data are collected at the employer-job level, reported wages do not include individual components from

[16] We provide a case study for assemblers and fabricators in Appendix A.4 to demonstrate that the BLS job levels summarize job differences that are similar to the job levels in the German data that we explore in the previous section.

[17] See Bureau of Labor Statistics, National Compensation Survey, https://www.bls.gov/ncs/home.htm, for a detailed discussion of the NCS data and the job-leveling scheme. The BLS job-leveling scheme is distinct from its occupational coding, although some of the information used for the occupational coding and job leveling overlaps. Occupational classification schemes such as the Standard Occupational Classification (SOC) System used by the BLS differentiate jobs according to the tasks but not according to the level of complexity, so that occupational codes do not imply a hierarchical ordering but a horizontal differentiation. We provide corresponding evidence based on the German occupational coding (KldB) discussed in Appendix A.2.

Table 3: Mean wages in 2015 by job level and occupational group

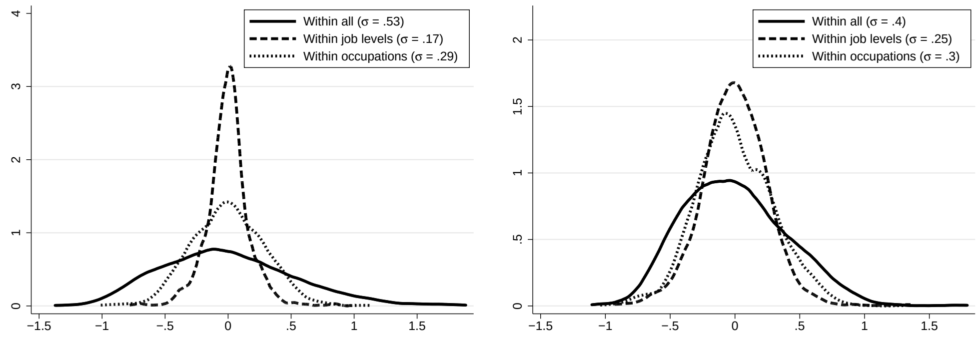
	Occupational groups (SOC)					
Level	11-29	31-39	41-43	45-49	51-53	All
All	38.22	12.58	17.34	23.09	17.87	23.25
1		8.55	9.63		10.01	9.25
2		9.63	10.53	14.26	12.09	10.48
3	13.01	11.15	12.83	14.78	15.62	12.89
4	15.42	13.67	16.32	18.23	19.67	16.39
5	18.80	18.84	20.14	21.11	20.95	20.13
6	20.96	21.83	24.42	27.47	24.92	23.77
7	24.63	28.03	30.56	30.67	31.27	27.17
8	32.11	33.14	38.82	34.12		32.92
9	37.50		62.13			38.32
10	42.68					44.55
11	50.65					53.26
12	69.37					73.13

Notes: Mean wages by job level and occupational groups from the 2015 National Compensation Survey. Occupational groups follow the 2010 SOC codes. The different occupational groups correspond roughly to Management, Business and Finance, IT and Engineering, Education, Legal, Healthcare (11-29), Service (31-39), Sales and Administration (41-43), Farming, Construction, Maintenance (45-49), and Production and Transportation (51-53). See SOC classification for further details. Missing fields indicate the case of too few observations for a combination of job level and occupational group to be reported by the BLS. These estimates are currently not published by the BLS and have been provided by the BLS upon request.

overtime pay, bonuses, or other sources so that variation within job level is absent at the establishment level. This likely explains the even higher explanatory power of observables for cross-sectional wage dispersion compared to the SES data. When all employer and job information is included, observables account for 85% of cross-sectional wage dispersion ($R^2 = 0.847$, Pierce (1999), Table 4), and job-leveling factors alone account for 75% of wage variation. These results corroborate key findings from our previous analysis of SES data. First, employer surveys with detailed job characteristics deliver high explanatory power on wage dispersion, and second, the job characteristics are a key contributor to the high explanatory power of wage dispersion in these data.

Additionally, we explore the relationship between occupational wage differences and job-level wage differences in the NCS data. The BLS provides information on average wages by job level both across and within occupations. Table 3 shows mean wages by job level

Figure 9: Wage density across occupations by job level



(a) U.S. wage dispersion (b) German wage dispersion

Notes: Density estimates for residual wages by occupation and job level. *Within all* shows residual wage density after removing the average wage, *within job levels* removes average job level wages, and *within occupations* removes average wages by occupation. Wage observations are for occupation-job-level cells. See text for further details. For Germany, we observe 601 occupations and 5 job levels. For the United States, we observe 269 occupations and 15 job levels.

and occupational group from the 2015 NCS.[18] We see that within coarse occupational groups, there is a wide variation in wages across job levels. For example, looking at all jobs and going from job level 3 (paying on average 13 dollars) to job level 8 means a wage increase of 20 dollars per hour. Climbing further to job levels 10, 11, and 12 will lead to stellar wage increases of 30, 40, or 60 dollars per hour. If anything, these data suggest that climbing the career ladder is more important in the United States than in Germany. We also note that when looking across occupation groups, the first occupation group (11-29), which includes management occupations, has on average much higher wages than the other groups. Interestingly, once we condition on the job level, the occupation group (11-29) tends to have below average wages. Generally, we find that the relative wage differences across occupation groups are small and (with one exception) less than 20% once we condition on job levels. In fact, raw differences in occupational wages are largely driven by differences in the average job level of an occupation, as shown by Pierce (1999) and discussed in Appendix A.3.

We use tabulated results from the NCS to further explore the differences between occupations and job levels in accounting for wage differences. We provide the corresponding evidence for Germany based on the SES data. Figure 9 shows a decomposition of wage differences across occupations and job levels for the 2010 NCS and the 2014 SES data. In both cases, we use average wages by occupation-job-level cell. We focus on 2014 SES data because of the finer four-digit occupation codes (KldB classification) in these data:

[18]These estimates are currently not published by the BLS and have been provided by the BLS upon an individual request for data.

we observe 601 different occupations and 5 different job levels.[19] This implies that the number of occupations is 120 times larger than the number of observed job levels in the German SES data. In the U.S. NCS data, we observe 269 occupations and 15 job levels. The ratio between occupations and job levels is still large with 18 times more occupations than job levels. Figure 9 shows density estimates for residual (log) wage for three cases. In the first case, we remove average wages; that is, we show the variance of (log) wages. This is shown as case *within all*. Second, we remove average wages by job level. This is shown as the case *within job levels*. Finally, we remove average wages by occupation. This is shown as the case *within occupations*. The legend also reports the estimated standard deviation for each case.[20] In the U.S. case, the 15 job levels account for roughly two-thirds of the cross-sectional standard deviation while 269 occupations account for only about a third of the cross-sectional wage variation. For the German case, the findings are even more striking. The 5 job levels account for about 40% of the cross-sectional variation, while 120 times as many occupation dummies (601 occupation codes) account for only about 25% of the cross-sectional wage variation.[21] In Appendix B.5, we document that even finer five-digit occupation codes resulting in 984 occupation dummies still account for less of the cross-sectional wage dispersion across occupation-job-level cells than 5 job-level dummies.

5 Determinants of careers: Human capital and luck

In our decomposition, we find a key role of the career ladder in shaping wage growth and inequality dynamics. This section explores the determinants of careers. In a first step, we consider the question of how important broadly defined human capital investment is for progression on the career ladder. In a second step, we investigate whether there is also a role for luck in shaping workers' careers. For this second step, we look at one particular source of luck, namely, the role a worker's coworkers play in climbing the career ladder. In a third step, we explore the relationship between labor market mobility and steps up and down the career ladder.

Workers invest in their human capital through a wide variety of channels. We consider education, experience, and labor market mobility. Education in school or college is probably the most common form of human capital investment. Learning by doing

[19] In Appendix B.5, we report results for ISCO occupation codes where we observe 118 occupations and for five-digit KldB occupation codes where we observe 984 occupations. The same conclusions arise.

[20] We use unweighted estimates across cells because the BLS does not release cell sizes for these data.

[21] In the analysis before, we decompose the increase in wage dispersion over the life cycle, while here we decompose the level of cross-sectional variation.

and on-the-job experience with an employer (tenure) are other forms of human capital investment that can be instrumental for successful careers. The third channel for human capital investment is the search for an employer that provides a good match with the worker.

5.1 Role of education

Table 4 provides a descriptive analysis of the relationship between education, experience, and the career ladder. We report by age groups the shares of workers at different job levels conditioning on workers' educational attainment. We look at a younger age group with workers ages 25 to 35 and an older age group with workers ages 35 to 45. We further separate male and female workers. This simple descriptive statistic offers three interesting results. First, education and job levels are different. We find for all age groups that each education group has significant shares of workers (10%) across at least three job levels. Second, education is positively correlated with job levels. Workers with higher levels of education are found further up the career ladder. Typically, 60% or more of workers with only secondary education are at the two lowest job levels (UT+TR). For workers with a college education, we find that typically 60% or more are at the two highest job levels (PR+MA). Third, the distribution across job levels shifts to the top as workers age. For male and female workers across all education groups, workers in the age group 35 to 45 are more likely to be found at higher job levels than workers from the younger age group. For college-educated men the share of workers in management jobs (MA) doubles from 20% to 40% when comparing the two age groups. This fact again highlights the difference between education as a (typically) fixed worker characteristic after labor market entry and job levels that change over the course of the life cycle. The descriptive analysis suggests that education and experience help with progression on the career ladder and that females progress more slowly than men.

5.2 Role of luck

The results on education suggest that human capital investment is an important driver of careers. However, as we show next, the conclusion that there is no role for luck in career progression is not warranted. To explore the role of luck, it is useful to be able to interpret job levels cardinally. The estimated wage differences between job levels, the *job-level wage*, provide such cardinal measure. An OLS regression of job-level wages on worker characteristics achieves a degree of statistical determination in the ballpark of 30%, the usual range of what worker characteristics account for in terms of wage inequality,

Table 4: Share of hierarchy levels within formal education and age groups

	at ages 25-35 (in %)					at ages 35-45 (in %)				
Education	UT	TR	AS	PR	MA	UT	TR	AS	PR	MA
Males										
Secondary	25.6	37.9	26.7	7.8	2.1	18.3	39.7	29.7	9.2	3.0
Vocational	5.5	15.7	60.7	15.7	2.5	3.5	12.7	52.4	24.6	6.8
University	1.2	2.8	27.5	48.6	19.9	0.4	1.2	13.8	44.9	39.7
Other	17.9	28.9	38.3	12.1	2.8	12.8	27.3	36.2	16.4	7.3
Females										
Secondary	30.1	31.3	28.0	8.8	1.8	34.9	35.8	21.4	6.2	1.8
Vocational	5.7	13.0	64.3	15.2	1.9	6.3	13.7	57.2	19.8	3.0
University	1.9	4.6	35.0	40.3	18.1	0.9	2.9	25.1	43.9	27.3
Other	20.2	24.2	42.7	10.9	2.0	27.1	25.7	33.8	10.6	2.9

Notes: Relative frequencies across hierarchy groups in percentage points for different age groups. The top part of the table shows male workers, the bottom part female workers. Shares sum within age groups to 100. "Secondary" refers to workers with secondary education but no vocational training. "Vocational" refers to workers with secondary education as well as a vocational degree. "University" refers to all workers with a university or technical college degree. Workers without reported education are in the "Other" group. Hierarchy groups UT/TR/AS/PR/MA refer to untrained, trained, assistants, professionals, and managers, respectively.

leaving room for other elements including luck as determinants of career progression.

As one source of luck, we consider the effect of coworker characteristics on career progression. Although workers can change employers and coworkers over time, coworker characteristics can still be considered largely beyond a worker's control. The fact that coworkers influence workers' labor market outcomes has already been demonstrated in the literature. For example, Buhai et al. (2014) establish that not only a worker's own tenure but also the relative ranking among coworkers play a role in workers' wages. Similarly, we know from Jäger (2016) that the wages of workers and the probability of moving within a plant to better-paid jobs increases if coworkers leave the plant (in his case, because of death).

We estimate the effect of the experience ranking within a plant among a group of peers that might effectively be competitors for career progression. We consider two measures for the experience ranking. In the first case, we include a dummy only for the most-experienced worker within each peer group. The estimated coefficients quantify a *silverback effect*—the effect of being the most or more experienced member of the peer group on job-level wages. In the second case, we use what we refer to as the *experi-*

Table 5: Being the silverback: the effect of experience ranking on job-level wages

	Relative experience			
	Silverback effect		Experience rank	
Education group specific effects	Yes	No	Yes	No
More experienced than peers	2.5***	1.9***	1.6***	1.5***
× only secondary education		-0.1		1.7***
× college education		2.2***		-0.1
× other education		0.9**		-0.3
N	343,002	343,002	343,002	343,002
adj. R^2	0.51	0.51	0.51	0.51

Notes: The table displays the coefficients of an OLS regression of the log job-level wage, as defined in the main text, of a worker (multiplied by 100) on two sets of controls for experience ranking within peer groups of workers. A worker's peer group is all workers at the same plant who are at least as old and up to five years older and have the same educational attainment. Experience ranking controls are described in the text. The regression sample includes all male workers ages 45 to 50. The baseline group for the case with education-specific effects are workers with apprenticeship training. All regressions include a constant, education dummies (coefficients not reported), and plant fixed effects. *, **, *** indicate significance at the 10%, 5%, and 1 % levels, respectively.

ence rank. For the experience rank, we follow Buhai et al. (2014) and construct it as $\log(N_i + 1 - r_i) - \log(N_i)$ where r_i is the experience rank of worker i within the worker's peer group and N_i is the number of members in worker i's peer group. For example, the most experienced worker within each peer group has experience rank $r_i = 1$, and the least experienced worker has $r_i = N_i$. We get that within each peer group, the experience rank varies between $[-\log(N_i), 0]$. We restrict the sample to male workers because of the different career dynamics for females after age 30. We define a worker's competitive peer group within a plant as the group of workers who are at most five years older than the respective worker and who have the same educational attainment. We construct within each age-education cell of the plant the most experienced worker dummy and the experience rank. We regress job-level wages on the controls for the experience ranking. Table 5 shows the estimated coefficients from the regression with the job-level wage as the dependent variable.

On average, we find the *silverback effect* to be statistically significant. The more experienced a worker is, the higher he is on the career ladder. The first two columns show average effects. In the first case, considering only the most experienced worker, we see a statistically highly significant coefficient of 2.5, and for the second case, using the experience rank, we also get a highly significant coefficient of 1.6. These effects are also economically significant. The coefficient for the *silverback effect*, for being most experienced worker, implies that the job-level wage is 2.5 log points higher if a worker is the most experienced worker within his peer group. To put this into perspective, the job-level component accounts for approximately 25 log points in wage growth for 45- to 50-year-old workers, such that being the silverback of a group increases the job-level wage by roughly 10%. To quantify the effect of the experience rank, note that the average number of members within a peer group is 11. Hence, the difference in the job-level wage between the least experienced member and the most experienced member in an average peer group is 3.8 log points, 15% of the average job-level component at that age.

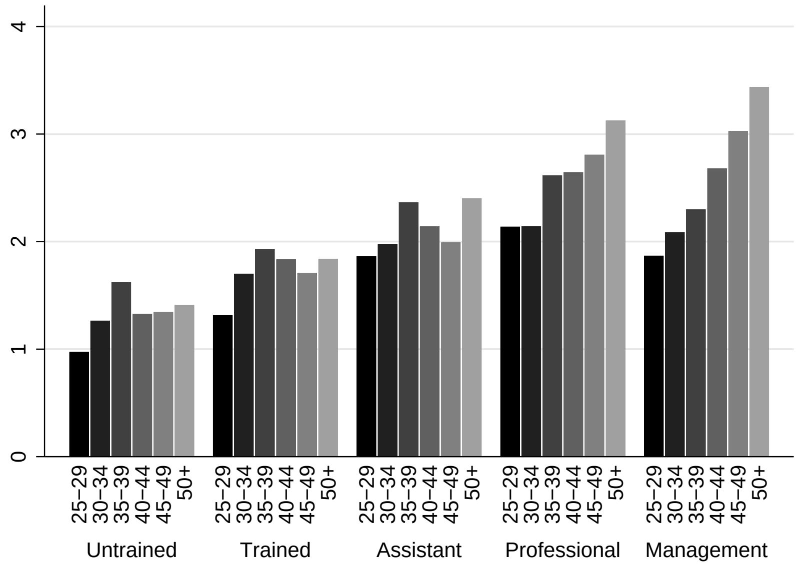
The last two columns of Table 5 report education-specific coefficients with workers who have an apprenticeship training forming the baseline group. We find some evidence that coworker effects are heterogeneous across education groups, but the (total) effect of being the more experienced peer is statistically significant in all groups. We interpret these results as supportive of the idea that there is a significant element of luck in careers because we find significant effects from coworkers on career progression.

5.3 Labor market mobility and career dynamics

As a final step, we explore how important labor market mobility and employer switching are for career progression. Labor market mobility across employers is another form of human capital investment. Table 4 suggests that although general experience accumulation is important for career progression, the accumulation of experience on-the-job with the current employer, the accumulation of employer tenure, might also be important for climbing the career ladder. Figure 10 shows how much tenure increases (in years) from one five-year age group to the next five-year age group, at different job levels. If all workers stayed with their employer, the increase between age groups would be five. We find that tenure tends to increase more strongly at higher job levels and that the increase accelerates over workers' careers. The steeper increase across job levels and age suggests that many workers climb the career ladder while staying with their employer.

To further address the question of the importance of employer switching for career dynamics, we rely on panel data from the SOEP, which allows us to follow individual workers over time. Together with demographics and income, the SOEP provides information on the individual labor market situation (Goebel et al., 2019). The data cover the period from 1984 to 2015. As part of these data, the SOEP collects information on job levels similar to the coding in the SES data but not directly comparable. The limitation of the coding in the SOEP is that it is based on ideas from the sociological literature

Figure 10: Tenure increase by age and job level



Notes: The figure displays the average additional years of tenure of an age group relative to the preceding one by job level. Averages over all sample years are shown for both males and females. For 25- to 29-year-olds, the figure shows the average number of years of tenure in the group.

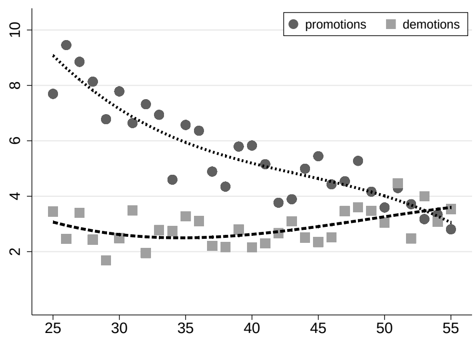
(Hoffmeyer-Zlotnik, 2003), and as such it loads more heavily on education and therefore tends to bias downward worker mobility across job levels.[22] With this caveat in mind, we use the job level from the SOEP data to explore worker mobility and career progression. To align the SOEP sample and the SES sample, we keep workers ages 25 to 55 working at employers with 10 or more employees. We drop self-employed workers, apprentices, military personnel, and public service workers. We drop all observations with missing information on job level, industry, education, occupation, or number of employees at their employer. Data are at an annual frequency, and we explain below how we define labor market mobility events.

In the first step, we construct life cycle profiles of promotion and demotion rates. Promotions (demotions) are naturally coded as a change in the job level from the current survey date to a higher (lower) job level at the next survey date. Figure 11 reports estimated annual promotion and demotion rates for males and females by age. We find declining promotion rates for both genders during the working life, in line with a concave wage profile. Males show higher promotion rates in the first part of the life cycle. At age 55, the levels for males and females have converged. Demotion rates are strikingly constant during the working life, and levels are very close between males and females.

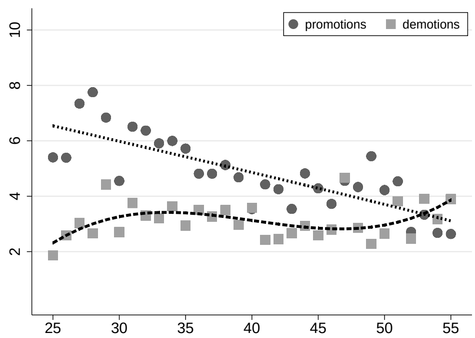
[22] Conditional on the job level, the SOEP data show quantitatively similar wage differences between job-level age profiles, as found in the SES data. We provide further details in Appendix D.

For both, demotion rates are substantially below promotion rates at the beginning of the working life, in the late 40s, the levels of promotion and demotion rates roughly converge, implying no further net career progression. In Appendix D, we compare net promotion rates, promotion rates minus demotion rates, for males and females, where in Figure 28, we show that net promotion rates diverge most strongly between ages 25 and 35, in line with the widening job-level wage gap documented in Section 3.

Figure 11: Promotion and demotion rates by age



(a) Males



(b) Females

Notes: Annual promotion and demotion rates by age for males and females based on SOEP data, years 1984-2015. All rates are shown in percentages. The left panel shows promotion and demotion rates for males, the right panel the promotion and demotion rates for females.

To see how labor market transitions are associated with career dynamics, we define four mobility events. We assign a worker with an employer change if the person is employed at both survey dates but is employed for less than one year with the current employer at the second date. We define a transition through nonemployment if a worker is nonemployed at the first survey date but employed at the second survey date. We assign an occupation change if workers answer positively to the question of whether "there has been a change in their job" and the recorded occupation changed.[23] Finally, we define the group of stayers as those workers who do not change employers or go through nonemployment. Using these mobility definitions, we ask whether promotions and demotions happen with the same employer or whether labor market mobility is a key driver of promotion and demotion dynamics.

Table 6 shows the share of all promotions and all demotions accounted for by stayers and movers. We find that more than 70% of promotions happen for workers who stay with their employer, while less than 30% of all promotions are associated with a change

[23]We condition on the information of job change to reduce measurement error in the occupation codes. It is well known that occupation codes are prone to be recorded with error so that occupational changes are too prevalent in household survey data (Kambourov and Manovskii, 2013).

Table 6: Promotions and demotions for stayers and movers

	employer change (%)	stayer (%)
promotion	28.6	71.4
no change	11.8	88.2
demotion	38.1	61.9

Notes: Shares of all promotions and demotions that happen for workers staying with the same employers during the year (column *stayer*) and workers changing employers (column *employer change*). Each row sums to 100%.

in employers. For demotions, we find a similar distribution: about 60% of demotions happen at the same employer, while 40% involve a change in employers.

In the next step, we explore promotion and demotion rates conditional on labor market transitions. Table 7 reports the distribution of promotions, demotions, and lateral moves conditional on employer changes, transitions through nonemployment, and occupation changes. We report stayers and averages as a reference.

Table 7: Promotions and demotions for labor market transitions

	employer change (%)	non-employment (%)	occupation change (%)	stayer (%)	average (%)
demotion	6.6	10.7	11.0	2.2	3.0
no change	84.5	77.3	75.6	93.6	92.0
promotion	9.0	12.0	13.5	4.2	5.0
net promotion	2.4	1.3	2.5	2.0	2.0

Notes: Promotions and demotions for different mobility events (see text for details). Each column shows a mobility event and the share of workers conditional on this mobility event who have a promotion or demotion. The row *net promotion* reports the difference between promotion and demotion rates for each mobility event. The first three rows (excluding net promotions) of each column sum to 100%.

The results support the idea that labor market mobility implies more movement along the career ladder. We find that both employer changers and workers that go through nonemployment exhibit more mobility on the career ladder compared to job stayers. We find that 9% of all employer changes involve a promotion, in line with the idea that workers move to another employer to climb the career ladder. Yet, we also find that 7% of employer changes are associated with a demotion. On net, workers with a change in employer have a 20% higher than average net probability of career progression (*net* *promotion* = promotion − demotion rates). Perhaps surprisingly, we also find that 12% of nonemployment transitions involve a promotion. The promotion in this case is relative to the last job before nonemployment; that is, here we look for at least two-year changes in job levels. Since 11% of all nonemployment transitions involve a demotion, on net, workers after a nonemployment spell experience slower career progression than any other group. Their net promotion rate is 35% lower than the rate of the average worker—without taking into account here that the rate refers to a longer time span between job observations. We observe the strongest career progression for occupation changers, who have a 25% higher net promotion rate than the average worker. Notwithstanding, a change in occupation does not involve a promotion for 87% of all occupation changers (11% demotions, 76% lateral moves). Looking at job stayers, we find that there is substantially less mobility on the career ladder: only 4% of workers move up the career ladder each year, and 2% move down. Stayers account for the large majority of workers, and therefore, largely determine average promotion and demotion rates in the German labor market (Table 6).

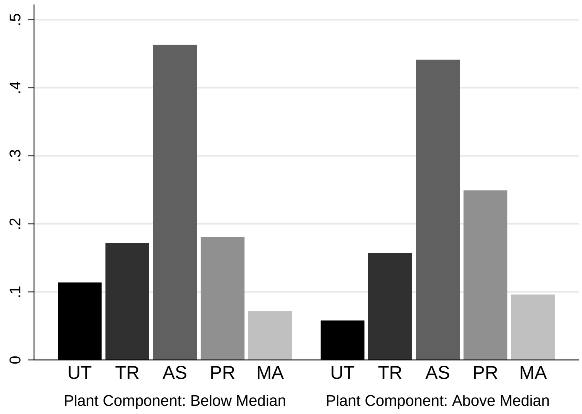
6 Organizational structure and plant wage differences

Our decomposition in Section 3 finds that the plant component does not account for much of the increasing wage dispersion over the life cycle. At the same time, recent evidence for the United States finds firm differences to be a key driver of increasing wage inequality over the past 30 years (Song et al., 2015). At first glance, these two pieces of evidence do not seem to align well. However, we have seen that the plant component and the job component are positively correlated and increasingly so over a worker's life cycle. This implies that the plant component will pick up the organizational structure of plants if we do not control for the composition of jobs in our decomposition.

Figure 12 reports the distribution of workers across job levels for plants sorted by the estimated plant component $\tilde{\zeta}_p$. Well-paying plants offer on average more jobs at higher job levels, and only low-paying plants offer a substantial fraction of jobs on the lowest two job levels. This echoes the findings of Tåg et al. (2013) for Sweden. Recall that the plant component captures whether plants pay better *at all* job levels; that is, the plant component is not driven by having a larger share of top-level jobs. Well-paying plants are on average also substantially larger such that the top third of all plants (by plant component of wages) employs 50% of all workers.

If we repeat the decomposition for wages leaving out the job component (see Figure 13(a)), we get a decomposition that suggests very different conclusions compared to our baseline decomposition that accounts for job differences. We consider males here and

Figure 12: Shares of employees by job level and plant component



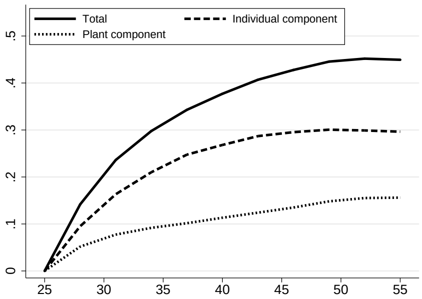
Notes: The figure shows the share of workers by job levels in plants with below- or above-median estimated plant component $\tilde{\zeta}_b$. The median is defined on a worker basis. 67% of all plants have a below-median plant component.

relegate results for females to Appendix B.4. The general conclusions apply to both genders equally.

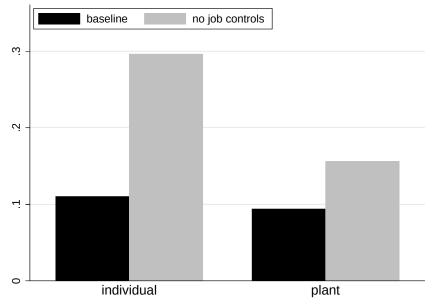
First, a substantially larger fraction of wages remains unexplained. More importantly, dropping the job component leads to an estimate of the role of differences between plants for wage growth that is 50% larger than in our baseline, as Figure 13(b) shows. When we decompose the increase in wage dispersion over the life cycle, we find a qualitatively similar shift in results (see Figure 13(c)). Now, the contribution of plants to wage inequality is 20% larger than in the baseline and both education and plant differences contribute significantly to the increase in wage dispersion over the life cycle (see Figure 13(d)). Together, the individual and plant components explain roughly 8 out of the 15 log point increase in the wage variance. The covariance between the individual and plant components also contributes to the growth in wage inequality by 2 log points (not displayed).

Our results shift the reasons for why employers are important for life-cycle wage dynamics. They primarily matter not because of their wage-level differences but because of their differences in organizational structure and associated differences in career opportunities. These differences in organizational structure are correlated with average plant wages and get partly picked up by the plant component when organizational structure is unobserved. While we find wage growth and wage dispersion to be unrelated to the plant itself, the organization of the plant in terms of its job structure is likely an important determinant of workers' decisions about where they want to work.

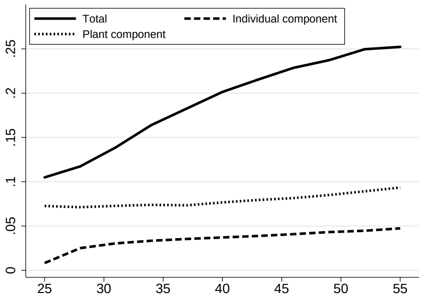
Figure 13: Decomposition of wage growth and variance of wages by age (males), ignoring job controls



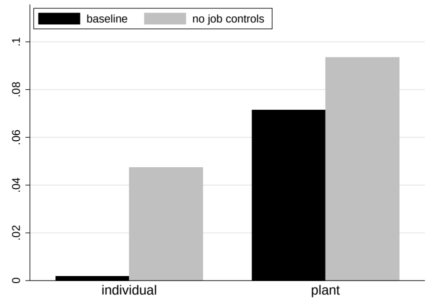
(a) wage growth decomposition



(b) comparison growth contribution



(c) wage variance decomposition



(d) comparison variance contribution

Notes: Top row shows the decomposition of male wage growth in the individual and plant components. The bottom row shows the corresponding decomposition of wage variances for males. The left panels show the life cycle profiles when estimating the components without job controls. The right panels compare the components at age 55 to the baseline decomposition that includes job controls (job components not shown here).

7 Conclusions

This paper explores four different microdata sources and documents a key role for jobs in accounting for life cycle wage dynamics and wage differences across workers and employers in the macroeconomy. When decomposing life cycle wage dynamics in German administrative data, we find a key role for career ladder dynamics, job-level changes over a worker's career. Job levels provide a one-dimensional summary statistic that vertically differentiates jobs regarding the responsibility, complexity, and autonomy associated with a job's tasks and duties. Career ladder dynamics account for 50% of wage growth and virtually all of the increase in wage dispersion over the life cycle. Looking at the determinants of successful careers, human capital investment appears to be a necessary condition for high wages, but it is not sufficient. We provide evidence that the organizational structure of the production process shapes wage dynamics and that luck therefore also plays an important role. Specifically, we document a statistically and economically significant *sil-*

verback effect: being a more experienced worker in a group of peers improves the chances of ending up higher on the career ladder. We also document that labor market mobility is associated with career progression but that most steps up and down the career ladder happen with the same employer.

We think the documented importance of jobs and their characteristics for wage differences in the macroeconomy has implications for at least three strands of economic research. First, it has implications for research exploring secular trends in the wage structure. When employers create new jobs and assign new tasks and duties to jobs to reorganize their production process, they do this taking the macroeconomic environment into account. Their organizational decisions likely depend not only on available technologies, but also on the skill set of the current and future workforce and labor market institutions (Acemoglu, 2003). Our results highlight the interplay between skills, technology, and organization for understanding secular changes and cross-country differences in the wage distribution and wage dynamics (see also Caicedo et al., 2018).

Second, our findings scrutinize the prevalent assumption in labor market search models that jobs are drawn from a fixed distribution of job types without rivalry in their availability. Our finding that coworkers affect career progression and wages suggests that rivalry for jobs is important. Staffing and promotion decisions of employers are—to some extent—like playing musical chairs, where filled jobs become unavailable to other workers. Such externalities offer a new motive for labor market mobility across employers. Our results must therefore not be read as evidence against job search being important but rather as a shift in focus from search for contemporaneous high pay toward search for better career opportunities in the future, similar in spirit to Postel-Vinay and Robin (2002). The results furthermore point to strong job specificity of productivity: when a firm-worker match dissolves, the vacant job persists for the firm and is only lost from the worker's perspective.

Third, our results appear relevant for macroeconomic models of consumption-savings decisions by heterogeneous agents as they shed new light on the determinants of wage dynamics. The career ladder suggests an intimate link between average life cycle wage growth and wage risk. Our results suggest that both wage growth and wage risks are unequally distributed in the population and that wage risks react systematically to organizational changes which in turn reflect macroeconomic conditions.

The importance of this feedback from the macroeconomic environment to wage dynamics is potentially an interesting avenue for future research. For example, since our evidence pinpoints changes in job levels as a key determinant of wage dynamics, and because career ladder dynamics show a pronounced life cycle profile, this feedback might offer a new angle for understanding the causal mechanisms behind facts documented in the labor literature. Examples are the gender pay gap that we touch on in this paper, the scarring effects of recessions on workers' careers (Oreopoulos et al., 2012), and earnings losses after worker displacement (Jacobson et al., 1993). Regarding secular trends, our results also demand more research to explore the changes in job composition relative to the changes in wages associated with jobs.

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A German Structure of Earnings Survey (SES)

A.1 Data collection and explanatory power of observables

The German Structure of Earnings Survey (SES) data are transmitted to the statistical offices directly from the human resources and payroll accounting departments of plants. Firms can use tailored software provided by the German Statistical Office or software modules as part of commercial human resource software packages (Statistisches Bundesamt, 2016). The data can therefore be considered to contain a minimum number of measurement errors. The high quality of the data is key to deliver the high degree of statistical determination in the wage regressions. Besides data quality, the other and economically more important reason for the high explanatory power is that we observe the job levels of a worker's job. The job level summarizes the responsibility, complexity, and autonomy associated with the tasks and duties of the job on a one-dimensional hierarchical scale. As we demonstrate in the main part of the paper, this job-level information has exceptionally high explanatory power for wages.

Table 8: Importance of characteristics in explaining hourly wages

	Plants	Job levels	Job levels and plants	Job levels, plants, occupations, education, experience, tenure, and sex	Job levels, plant size, region, and industry
(adj.) R^2	0.580	0.459	0.779	0.809	0.621

Notes: Adjusted R^2 of different regressions on log wages. All regressions contain year fixed effects as additional regressors. The first column regression is only on plant fixed effects, the second column only on job-level dummies, the third column on job-level dummies and plant fixed effects, the fourth column on job-level dummies, plant fixed effects, occupation dummies, education, experience, tenure, sex, and interaction dummies, and the fifth column on job-level dummies, plant size dummies, regional dummies, and industry dummies.

Table 8 shows the R^2 statistics from simple linear regressions of log worker wages on various sets of observables. Job levels and plants stand out in their importance when it comes to accounting for observed wage dispersion: five dummies for job levels account for close to 46% of wage variation in the macroeconomy. We report similar findings from a cross-sectional wage regression in the BIBB/BAuA 2012 employment survey where we run a regression on corresponding job characteristics and account for 44% of wage variation (Section 4). Pierce (1999) reports even higher explanatory power from a corresponding regression in U.S. NCS data. The higher degree of statistical determination in the U.S.

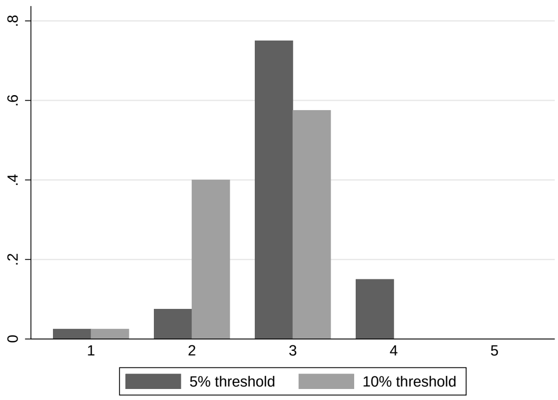
data is likely because the NCS data are at the job level rather than at the individual level, so that the data do not contain within job-level-plant variation in wages that could result from variable pay components. A corresponding regression to the one in Pierce (1999) in BIBB/BAuA data for white-collar workers accounts for 66% of wage variation across job-level points in data that is likely plagued by more measurement noise than administrative datasets such as the SES or NCS.

Table 8 also shows that the R^2 of the regression that combines both plant and job-level controls is smaller than the sum of the R^2 statistics of the separate regressions. This reflects the important correlation between plants and the composition of jobs (organizational structure) that we document in Section 6. When we add further controls, the R^2 increases to 0.81, but the additional explanatory power that we get from adding experience, occupation, education, sex, and employer tenure is modest at best.

A.2 Job levels and occupations

This section provides supplementary results to the discussion in Section 4 on the distinction between job levels and occupations. Here, we quantify the distribution of job levels across occupations, what we call the *hierarchical depth* of occupations. For the baseline, we consider two-digit occupations and measure hierarchical depth by the share of workers within each occupation on different job levels. We use 5% and 10% as two thresholds for hierarchical depth. An occupation has a hierarchical depth of 3 if on three job levels there are at least 5% (10%) of workers from this occupation. We report the shares of occupation by hierarchical depth in Figure 14. The figure shows that the typical (median) occupation has a hierarchical depth of 3.

Figure 14: Share of occupations with different hierarchical depth levels



Notes: Share of occupations with different levels of hierarchical depth. Hierarchical depth is defined as the number of job levels with at least 5% (10%) of workers from an occupation. Occupations are two-digit occupations.

Table 9: Cross-tabulation of job levels measured directly and job levels inferred from occupation codes

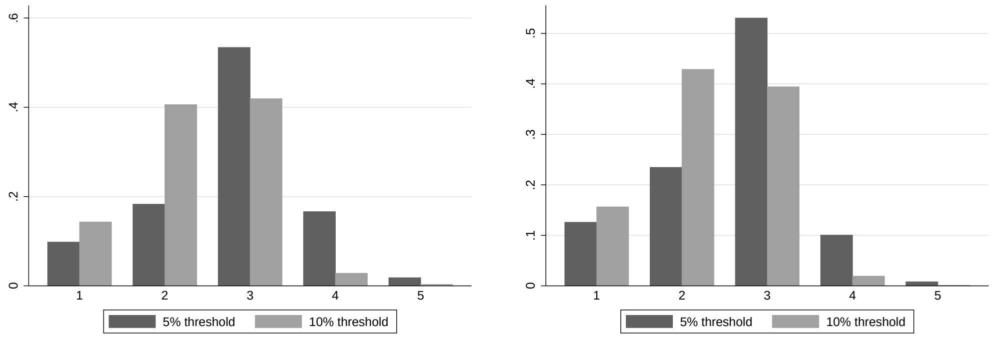
Complexity measured by occupation	Fraction of occupation (in %)	Fraction of job levels within occupation (in %)				
		UT	TR	AS	PR	MA
All	100	6.4	13.4	50.1	19.9	10.4
from last digit (KldB 2010)						
Helper	13.4	29.6	40.4	27.4	2.0	0.6
Trained	55.6	4.0	13.2	69.2	11.3	2.4
Specialist	15.8	0.7	2.9	35.8	50.9	9.6
Expert	15.2	0.5	1.1	14.7	34.7	48.9
using management occupations (KldB 2010)						
Supervisors	2.3	0.9	3.3	32.8	42.1	20.9
Managers	2.9	0.6	1.3	15.9	30.5	51.6

Notes: Cross-tabulation of job levels and job information provided by the German Statistical Office based on data from the 2014 Structure of Earnings Survey. Occupational information extracted from five-digit occupational code (KldB 2010). The first part of the table (*last digit*) shows the distribution of workers by occupational complexity across job-level groups. Shares sum to 100 within each row. The first column (*total*) shows the population share of the occupation group. The second part of the table (*management occupations*) shows the distribution of occupations coded as supervisors or managers across job-level groups. Shares sum to 100 within each row. The numbers in the columns refer to the share of workers coded as supervisors or managers in the total population.

Recent revisions of five-digit occupation codes have started to measure and encode job complexity (Helper/Trained/Specialist/Expert) (ISCO-08 or KldB-2010 for Germany). Table 9 shows a cross-tabulation of the last digits of the occupational classification system KldB2010 of the German employment agency against job-level information in the 2014 SES data. While the two are positively correlated, a substantial mass is still off-diagonal.

Figure 15 shows sensitivity results for hierarchical depth using the finer KldB2010 occupation classification. Figure 15(a) shows results using four-digit occupation codes and Figure 15(b) using five-digit occupation codes. In line with the results from above, we find that most occupations have a hierarchical depth of 3 with the only exception of the 10% threshold for the five-digit KldB codes in which case we find a marginally higher share of occupations with a hierarchical depth of 2. Still, we find that 40% of occupations have a hierarchical depth of 3 even with fine-grained five-digit occupation classifications and when requiring a 10% worker share. Using a 5% threshold, we find again that more than 50% of occupations have a hierarchical depth of 3.

Figure 15: Share of occupations with different hierarchical depth levels using KldB 2010



(a) four-digit KldB codes (b) five-digit KldB codes

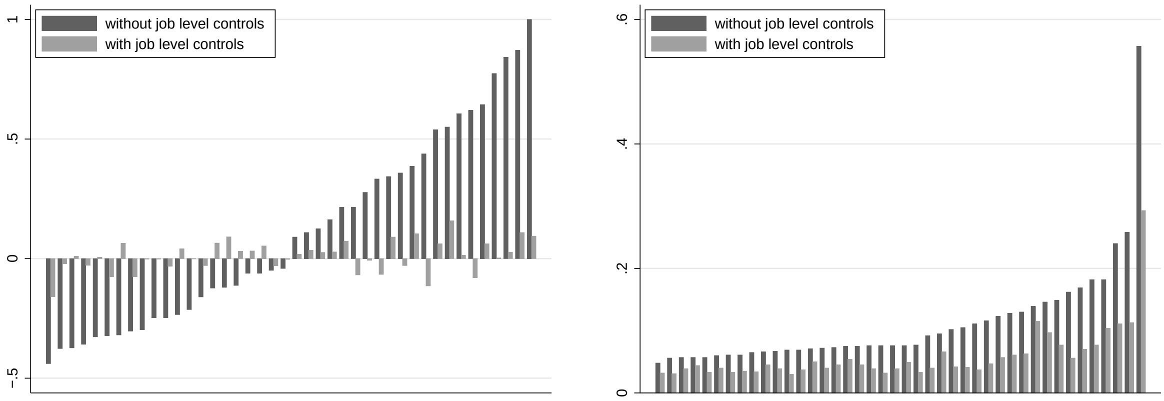
Notes: Share of occupations with different levels of hierarchical depth. Hierarchical depth is defined as the number of job levels with at least 5% (10%) of workers from an occupation. Left panel shows four-digit KldB codes. Right panel shows five-digit KldB codes. Occupation codes only available for 2014 SES data. Sample selection applies.

A.3 Job levels and occupations in the U.S. National Compensation Survey

The National Compensation Survey for the United States classifies all jobs according to their occupation and job level. Occupations are coded using the Standard Occupational Classification (SOC) System based on the skill levels and primary duties. For the job leveling, the BLS interviewers evaluate the duties and responsibilities of a job. The method used to classify jobs is *point factor leveling*, and it assigns points to particular aspects of the duties and responsibilities of the job. It also takes into account the skills, education, and training required for the job. Hence, there is some overlap among occupation codes. In contrast to the occupation coding, the job leveling aims to evaluate jobs with respect to required knowledge, job controls and complexity, contacts on the job in terms of nature and purpose, and a job's physical environment. Jobs are evaluated for each of these four factors, and the job level is the sum of level points from all four factors. Importantly, the job leveling is based on responsibility and not on assigned job titles in establishments. The BLS then groups jobs in up to 15 job levels. See the US Bureau of Labor Statistics (2013) Job Level Guide for further details.

Pierce (1999) also explores occupational wage premia and within-occupation wage differences after job characteristics are taken into account. The results are striking. He finds that most of the occupational wage differences disappear once job-leveling factors have been taken into account and that even within occupation groups, on average 50% of the wage dispersion can be accounted for by job-leveling factors. These findings align

Figure 16: Occupation wage premia and within-occupation wage dispersion



(a) occupation wage premia (b) within-occupation wage dispersion

Notes: Left panel: estimated occupation wage premia after controlling for employer and job characteristics with and without job-leveling factors in the National Compensation Survey (NCS). See text for details. Right panel: residual within-occupation wage variance after controlling for employer and job characteristics with and without job-leveling factors in the NCS. All estimation results are taken from Table 7 in Pierce (1999).

closely with our findings that occupations do not account for a large part of wage growth. Figure 16 visualizes results from Table 7 in Pierce (1999). Occupational wage premia are estimated as wage differences in the average occupation in a (log) wage regression that also controls for job attributes including and excluding job-leveling factors. Figure 16(a) shows occupations sorted by their estimated occupation-wage premium in the case that no job-leveling factors are included. The data show large occupational wage premia ranging from almost -0.5 to 1. After including the job leveling factors, the wage premia decline substantially. This suggests that a large part of occupation wage differences comes from different distributions across job levels within each occupation and the job levels themselves account for a large share of wage dispersion (Table 3). Closely related to that, Pierce (1999) finds that the within-occupation wage dispersion shown in Figure 16(b) is largely reduced when accounting for job-leveling factors. For within-occupation wage dispersion, Pierce (1999) finds that including job-leveling factors reduces wage dispersion on average by 50%. These results corroborate and strengthen our previous finding that job-leveling factors provide information on job characteristics independent of occupation information that accounts for substantial within-occupation wage dispersion.

A.4 Case study

To substantiate the differences between occupations and job levels and to highlight that these differences also apply beyond the German case, we consider a case study for a narrowly defined occupation group: assemblers and fabricators in production. For our case study, we start with the German union bargaining agreement for metal and steel workers in North-Rhine-Westphalia. This union bargaining agreement has at its core an analytic job-leveling scheme to assign workers to wage scales that is closely comparable to the BLS job-leveling scheme and which we use for our analysis in Section 4. Together with the job level, we also observe the bargained wage for each job level.[24] For assemblers (*Montierer*) and fabricators (*Maschinen- und Anlagenbauer*), we have job-leveling information that distinguishes these occupations in six different job levels: four job levels for the occupation group assemblers and two for fabricators.[25] We use this job-leveling information (i.e., specific job descriptions regarding tasks and duties of the jobholder) to assign job levels based on the BLS job-leveling guide. Using the resulting job levels, we assign wages for full-time workers from the tabulations for production occupations from the NCS in 2010.[26] In the NCS data, we stay within a single occupation group according to the classification in the 2000 SOC System and use only wages at different job levels. After leveling the German jobs using the BLS procedure, we remove mean wage differences between Germany and the United States so that the average across the assigned wages is one in both countries.

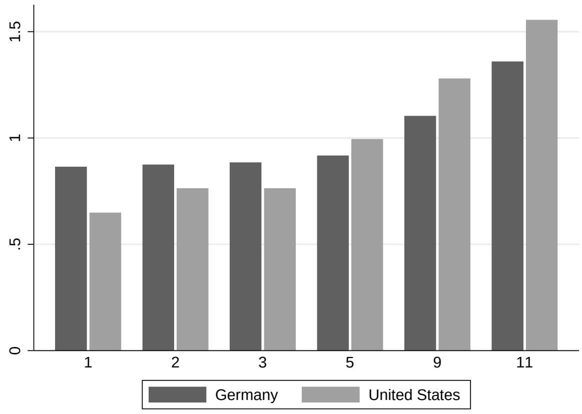
Figure 17 shows the standardized wage differences across job levels for Germany and the United States. We find that wage structures show a similar shape across countries, with the key difference that the German wage structure shows more wage compression especially in the lower part. This type of wage compression is typically associated with union wage bargaining in Germany. Overall, we find wages to be roughly flat across the first four groups in Germany and the first three groups in the United States, and find a positive gradient across the upper three groups. Hence, qualitatively the estimates for the corresponding U.S. jobs show a very similar pattern but show more wage dispersion overall. Part of the differences might be because job-level wages in the German collective bargaining agreement only include base pay, whereas they also include incentive and performance pay in the data for the United States, and because the wages for Germany are

[24] These bargained wages are lower bounds for wages and are typically supplemented by performance components that are worker and firm specific.

[25] One occupation has no directly assign occupation title but comes from the same task section (*Aufgabenfamilie*).

[26] United States Department of Labor, Bureau of Labor Statistics, National Compensation Survey — Wages, Table 8: Civilian workers: Mean hourly earnings for full-time and part-time workers by work levels, https://www.bls.gov/ncs/ocs/sp/nctb1482.txt.

Figure 17: Leveling wage structures assemblers and fabricators in production



Notes: Standardized wages for assemblers and fabricators in production for the United States and Germany. German wages are taken from the union bargaining agreement for metal and steel workers in Nordrhine Westphalia. Wages for the United States are derived using the BLS job leveling approach and NCS wage information by occupation and job level. The job levels are taken from the metal and steel workers bargaining agreement. See text for details.

only wages under the specific union bargaining agreement in one state that likely feature wage compression. Despite these caveats, we take this case study of a narrowly defined occupational group as further evidence for the importance of job levels and the associated vertical job differentiation for determining wages and wage differences in Germany and the United States.

B Sensitivity analysis and further results

We provide several sensitivity checks to our baseline analysis from the main part of the paper. In the sensitivity checks, we explore the effects of not being covered by a collective bargaining agreement, considering only full-time work, or focusing on large establishments. We also show results if do not drop public employers from the sample or when we do not control for individual fixed effects using the synthetic panel regression. We report additional results for women when we do not control for the job component and for the variance of the residual wage component over the life cycle for males and females. Finally, we report sensitivity results for wage dispersion across occupation-job-level cells using different occupation classification schemes.

B.1 Heterogeneous returns to job and individual characteristics

For the first set of sensitivity checks, we interact variables from the baseline regression in equation (3) with dummy variables for not being covered by a collective bargaining agreement, for working full-time, and for working in a large establishment. In Table 10, we compare the baseline sample to the part of the sample that gets a positive dummy in the sensitivity analysis. Overall, there are differences in the job-level composition in the alternative groups compared to the baseline sample, but they are not striking. We also report results for a sensitivity analysis where we do not drop observations from public employers and publicly controlled firms. Table 10 shows in the last column characteristics of workers and jobs at public employers that we drop for the baseline analysis. Two observations are noteworthy for this sample of public employers. First, the share of females is large: almost 2/3 of employees at public employers are female. Second, the job composition at public employers has fewer jobs at the untrained, trained, and assistant job levels but more jobs at the professional and management job levels.

Table 10: Summary Statistics

	baseline	no collective bargaining	only full-time	large plants	public employers
wage	18.9	17.8	19.9	22.0	19.4
age	41.1	40.6	40.8	41.3	42.1
female	38.9	37.9	27.2	37.3	61.9
UT	8.6	7.4	6.5	8.1	4.9
TR	16.4	19.0	15.3	14.3	7.0
AS	45.2	49.0	44.9	40.7	37.3
PR	21.5	17.3	23.5	25.6	29.3
MA	8.4	7.2	9.8	11.3	21.4
N (million)	2.4	1.3	1.9	0.9	1.4

Notes: Descriptive statistics of sample composition for baseline sample and subsamples considered in sensitivity analysis. The rows *wage* and *age* refer to the sample averages. The row *female* refers to the share of females in the sample; *UT*, *TR*, *AS*, *PR*, and *MA* show the shares for workers at the different job levels in the samples; and N is the number of observations in millions of the different samples.

In the first step, we consider the sensitivity analysis with respect to collective bargaining agreements, full-time workers, and large establishments and test whether the estimated coefficients on the additional interaction terms are statistically significant. Table 11 shows test statistics for three tests for the three different interaction specifications. The first row jointly tests all interaction coefficients. We find that insignificance can always be strongly rejected. When we look more closely at the different components, we find that the coefficients on the interaction terms with the variables of the job component (third row) are always strongly significant. The coefficients on the interactions with the individual component are insignificant in the *no collective bargaining* case and significant in the two other cases (second row). The main part of the paper finds that job levels are the key variable of the job component to account for both wage growth and dispersion over the life cycle. When we look at the coefficients of the interaction terms with the job-level dummies, we find them to be always strongly statistically significant except for large plants where they are significant at the 10% level (fourth row).

Table 11: Test statistics for coefficient tests

	no collective bargaining		only full-time		large plants	
	p-value	F-stat	p-value	F-stat	p-value	F-stat
all	0.00	2.3	0.00	2.6	0.01	1.5
individual	0.14	1.3	0.00	2.2	0.04	1.6
job	0.00	3.1	0.02	2.1	0.02	1.5
job level	0.00	16.0	0.00	4.7	0.07	2.2

Notes: Test statistics for joint significance of interaction coefficients with wage component coefficients. Row *all* shows test results for joint significance of all interaction terms, row *individual* shows test statistics for coefficients of individual component, row *job* shows test statistics for coefficients of job component, and row *job level* shows test statistics for the joint significance of the job-level interaction dummies. See text for further details.

This finding means that potentially there is a layer of heterogeneity that is deeper than what our baseline treatment explores. Yet, the test results in Table 11 only talk about statistical, not economic significance. The same careers (e.g., across job levels and occupations) can potentially mean something different when the coefficients (i.e., the returns to occupation and job level) are much different for full-time workers or workers not covered by collective bargaining.

Given the importance of the job component in the main part of the paper, we focus here on the changes in the job component when discussing the economic significance and sensitivity of our results. Figures 18(a) and 18(b) show the job component from the baseline specification together with the specifications from the different sensitivity specifications (no collective bargaining, full-time, large plants). We show the case in which we keep the evolution of the characteristics of jobs over the workers' life cycle as in the baseline sample, but treat them with the wage schedule for the subgroup for which we estimated the interaction terms. That is, we ask, what would the wage profile of workers look like if all got noncollectively bargained wages? Of course, this assumes that neither the career paths nor the wage schedule of non-collectively bargained wages would change when there is no collective bargaining. This has to be taken into account when comparing the different job components.[27] Similarly, Figures 18(c) and 18(d) show the contribution of the job component to the increase in the variance of log wages over the life cycle for the baseline and the different sensitivity specifications using the same technique. In contrast to the presentation in the main part of the paper, we removed level differences at age 25 for easier comparison.

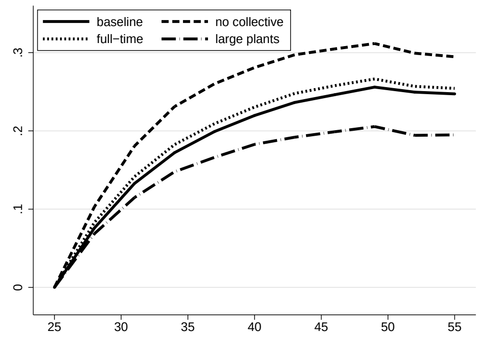
Looking first at the case of no collective bargaining, we find the age-wage profile (for the job component) would look steeper if no worker had collectively bargained wages. When looking at variances, we also find that job-level returns in wages are more diverse when the worker is not covered by a collective bargaining agreement so that without collectively bargained wages, wage dispersion would increase much more over the life cycle. This reflects the fact that there is wage compression in collectively bargained wages (see Section A.4 of this appendix). When looking at large plants, we find results that are opposite to *no collective bargaining.* Wage growth profiles are less steep, and wage dispersion increases less. The likelihood is that these plants have a larger fraction of workers with collectively bargained wages.

The effect of working full-time is more nuanced. In economic terms, this heterogeneity is negligible even if statistically significant. The average growth in the job component is stronger but without increasing the dispersion over the life cycle. In other words, the wage premia for full-time workers are larger in the middle of the job-level distribution AS to PR, but the hourly wages of the lowest and highest job levels are very similar across full-time and part-time.

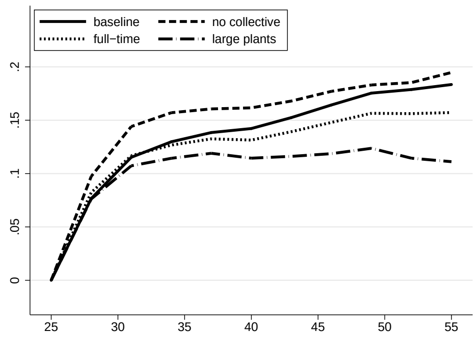
Figure 19 shows the effects from including public employers in the baseline sample. We perform the same decomposition for the larger sample as in the baseline analysis and compare the results for the job component from the larger sample to the baseline sample. We find that the job component slightly decreases for males but increases its contribution to the variance. The most notable effect is for females. Including public employers adds more than a third to the job component for female wage growth. This finding suggests that public employers are an important contributor to female career progression after age 35 and that females seem to select into public-employer careers. The effect on the increase in the variance is small and tends to decrease the contribution of career dynamics to wage dispersion for females.

[27]This assumes that there are no equilibrium effects on the organizational structure if there are, for example, only plants without collective bargaining agreements in the market.

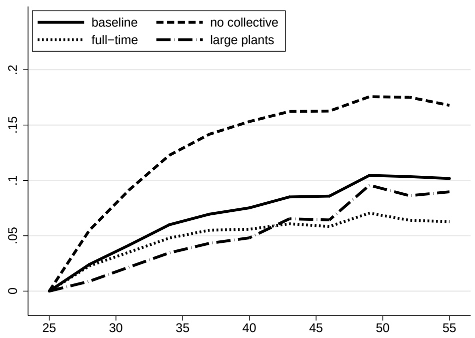
Figure 18: Contribution of job component to wage growth and wage dispersion over the life cycle



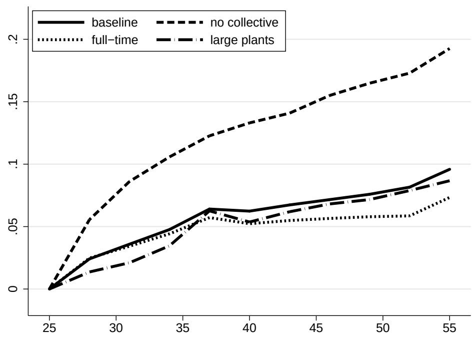
(a) Growth (males)



(b) Growth (females)



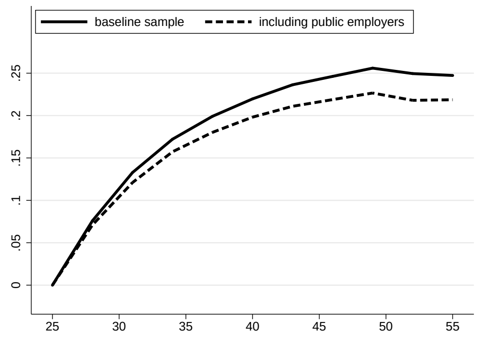
(c) Variance (males)



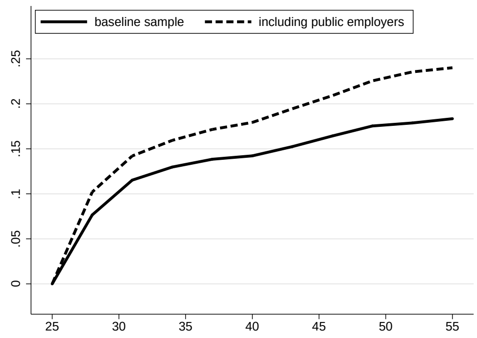
(d) Variance (females)

Notes: Contribution of the job component to wage growth (top row) and wage dispersion (bottom row) for males (left panels) and females (right panels). The solid line shows the job component for the baseline from the main part of the paper; the short dashed line shows the case with no collective bargaining interaction; the dotted line shows the case with full-time interaction; and the dash-dotted line shows the case with large firm interaction. Job components have been constructed by setting all dummy variables in the interaction terms to one. As in the main text, all graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as three-year groups).

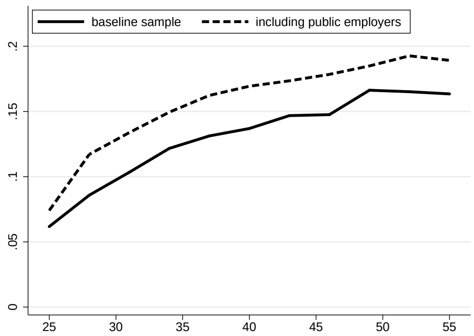
Figure 19: Contribution of job component to wage growth and wage dispersion at public employers



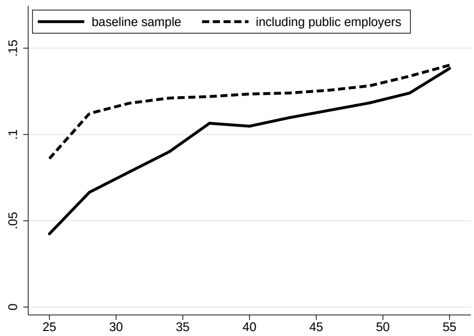
(a) Growth (males)



(b) Growth (females)



(c) Variance (males)



(d) Variance (females)

Notes: Contribution of the job component to wage growth (top row) and wage dispersion (bottom row) for males (left panels) and females (right panels). The solid line shows the job component for the baseline from the main part of the paper; the dashed line shows results for a sample including public employers and publicly controlled firms. As in the main text, all graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as three-year groups).

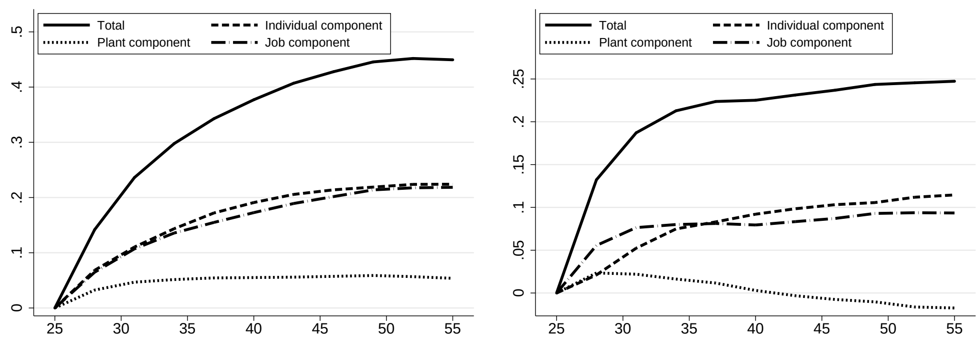
B.2 Pooled regression without individual fixed effects

The main part of the paper uses synthetic cohorts to control for individual fixed effects that are arguably correlated with education, career progression, and potentially employer types. In this section, we run as an alternative specification a pooled OLS regression controlling for cohort effects but not controlling for individual fixed effects. Specifically, we set $\hat{\gamma}_i = \gamma_c$ in equation (2) and run instead the following regression on the pooled data:

$$\hat{w}_{it} = \gamma_c + \beta_J \hat{J}_{it} + \beta_I \hat{I}_{it} + \hat{\epsilon}_{it}. \tag{5}$$

We proceed otherwise as described in the main part of the paper and use the same control variables for the job component J_{it} and individual component I_{it}. We also demean again at the plant level to construct $\hat{J}_{it}$ and $\hat{I}_{it}$. Figure 20 shows the decomposition of wage growth in the individual, plant, and job component if we do not control for individual fixed effects.

Figure 20: Wage decomposition for males and females without controlling for individual fixed effects



(a) Males (b) Females

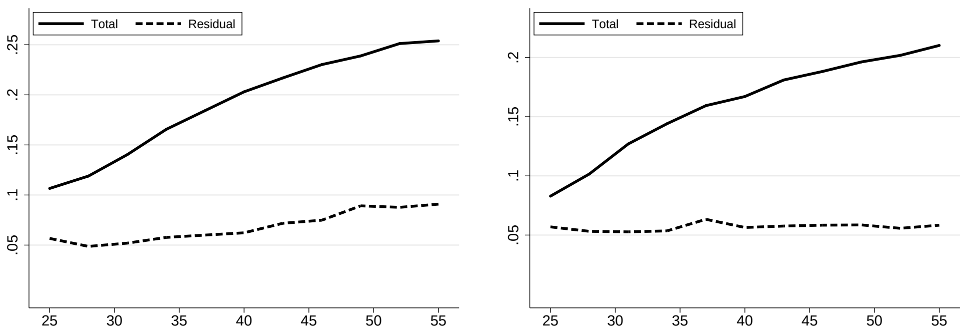
Notes: Decomposition of log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. Decomposition based on regression without controls for individual fixed effects. The dashed line corresponds to the individual, the dotted line to the plant, and the dashed-dotted line to the job component; the solid line (total) equals the sum over the three components. The horizontal axis shows age, and the vertical axis shows the log wage difference. As in the main text, all graphs show the coefficients of age dummies of a regression of the components on a full set of age and cohort dummies (ages defined as three-year groups).

Comparing the decomposition results for wage growth to the baseline results in Figure 2 shows that the key finding of the importance of the job component for wage growth over the life cycle is robust. We find that for both males and females, the contribution of the job component to wage growth is still most important if we do not control for individual fixed effects. If individual fixed effects are important for labor market outcomes, we should expect that estimated coefficients change from omitting this control variable from the regression. We find a sizable effect on the individual and plant components, which we interpret as an omitted variable bias from the individual fixed effect. The result that the job component is the driver of the increase in wage dispersion is also robust to omitting controls for individual fixed effects. We find that in the decomposition of the increase of wage dispersion the contribution of covariances between the three components become more important. We attribute these differences to the omitted individual fixed effect and do not report results here. These results are available from the authors upon request.

B.3 Residual Variance

We show the decomposition of life cycle wage dispersion for males and females in Figures 6 and 7. The wage decomposition contains a residual that is by construction zero on average conditional on age, but it might have an age-varying variance. A common approach to modeling wage dynamics interprets these residuals as the realization of wage risk (Lillard and Willis (1978), MaCurdy (1982), Carroll and Samwick (1997), Meghir and Pistaferri (2004), and Guvenen (2009)). Increasing life cycle profiles of the residual variance is through the lens of this approach interpreted as a stochastic process with a large and strongly persistent shock component, in the limiting case, even fully persistent. Figure 21 shows the variance of residuals from our decomposition. We find a small increase of less than 5 log points for males and virtually no increase for females. The very modest increase in the variance by age would be interpreted in the existing literature as providing little evidence for large and persistent wage shocks and that wage fluctuations over the life cycle are few and transitory.

Figure 21: Residual wage variance



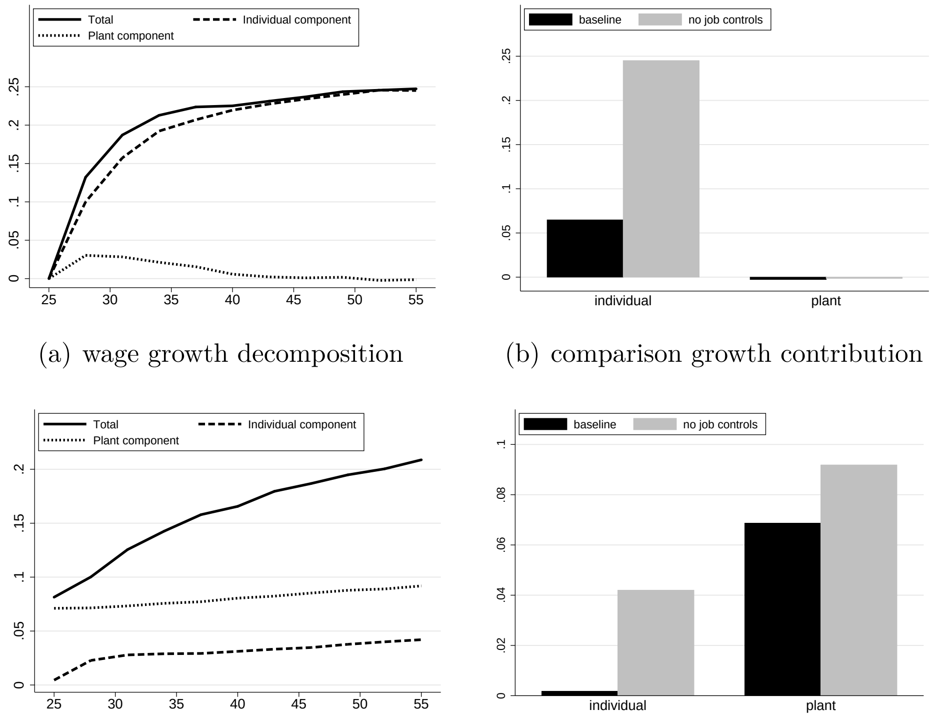
(a) Males (b) Females

Notes: Life cycle profiles of the variance of residuals from the wage decomposition in Section 3 for males (left panel) and females (right panel). The solid line shows the total variance of wages and the dashed line the variance of residuals from the wage regression in equation (2). Both graphs show the coefficients of age dummies of a regression of variances on a full set of age and cohort dummies (ages defined as three-year groups).

B.4 Decomposition of wage growth and wage dispersion without job information for females

Figure 22 shows the decomposition results for wage growth and wage inequality for females when ignoring job information. In Figure 13, we show the decomposition for men and discuss the changes in the decomposition from ignoring the job component. We find the same changes in the decomposition for females as we do for males, discussed in Section 6.

Figure 22: Decomposition of wage growth and variance of wages by age (females), ignoring job controls



(a) wage growth decomposition (b) comparison growth contribution

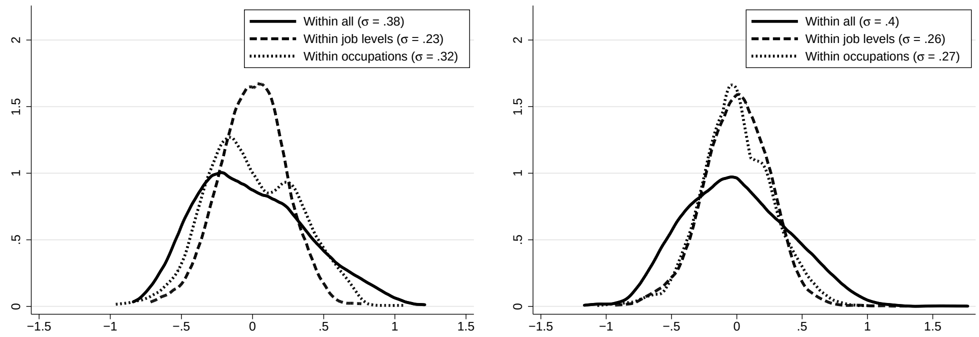
(c) wage variance decomposition (d) comparison variance contribution

Notes: The top row shows the decomposition of female wage growth in individual and plant components. The bottom row shows the corresponding decomposition of wage variances for females. The left panels show the life cycle profiles when estimating the components without job controls. The right panels compare the components at age 55 to the baseline decomposition that includes job controls (job components not shown here).

B.5 Job levels and occupations in 2014 SES data

In Section 4.2, we report estimated wage densities and standard deviations across occupation-job-level cells for the German 2014 SES data. For the baseline, we use four-digit KldB

Figure 23: Wage density across occupations by job level for different occupation codes



(a) three-digit ISCO codes (b) five-digit KldB codes

Notes: Density estimates for residual wages by occupation and job level. *Within all* shows residual wage density after removing the average wage, *within job levels* removes average job level wages, and *within occupations* removes average wages by occupation. Wage observations are for occupation-job-level cells. The number of cells varies with the occupation codes applied. See text for further details. For three-digit ISCO codes, we observe 118 different occupations and for five-digit KldB codes, we observe 984 occupations. We always observe 5 job levels.

occupation codes to define occupation cells. We demonstrate that the 601 occupation dummies account for less of the wage dispersion across these cells than five job-level dummies. Here, we demonstrate that this finding is robust to different occupation codes by presenting results for three-digit ISCO occupation codes and five-digit KldB codes. The ISCO codes are used in the decomposition analysis of life cycle wage dynamics as they can be constructed consistently over time. The KldB codes we use here are only available starting in 2014. Note that the number of occupation-job-level cells varies depending on the applied occupation codes. See Section A.2 for further details on the five-digit occupation codes.

Figure 23(a) shows results for three-digit ISCO codes with 118 different occupations. We find again that 5 job-level dummies account for 40% of wage dispersion across occupation-job-level cells while the 118 occupation dummies account only for about 15% of this wage dispersion. The difference becomes even more striking in case of the five-digit KldB codes in Figure 23(b). The 984 occupation dummies account for less of the wage dispersion across occupation-job-level cells than 5 job level dummies that account for 35% of the wage dispersion.

C BIBB/BAuA data and further results

C.1 Mapping of job-leveling scheme to survey questions

We use eight questions from the 2012 BIBB/BAuA employment survey to implement a job-leveling approach (Hall et al., 2018). Point values are taken from the leveling approach in the bargaining agreement for the steel and metal industry (Germany's largest industry) in North-Rhine-Westphalia (Germany's largest state). The collective bargaining agreement is the largest single one in the private sector in terms of workers covered ($\approx 700,000$). The point system can be downloaded in English.[28] The job-leveling system has four components: required skills and knowledge, autonomy, cooperation and communication, and supervision. We identify the questions from the BIBB/BAuA survey that we consider to most closely correspond to the different components of the job-leveling system. We use the following eight specific questions for our job-leveling approach:

1. What kind of training is usually required for performing your occupational activity? (four answers)
2. Is a quick briefing sufficient to perform your occupational activity, or is a longer working-in period required? (two answers)
3. How often does it happen in your occupational activity that one and the same work cycle / process is repeated in the minutest details? (four answers)
4. How often does it happen in your occupational activity that you improve existing procedures or try out something new? (four answers)
5. Question on type of task performed (simple, qualified, highly qualified)
6. How often does it happen in your occupational activity that you have to communicate with other people in your occupational activity? (three answers)
7. Do you have colleagues to whom you are the immediate supervisor?
8. And how many are they?

For the job leveling shown in Figure 8, we use the following assignment of the points from the job-leveling system to answers from the BIBB/BAuA survey. The point range of the

[28]See METALL NRW: Verband der Metall- und Elektro-Industrie Nordrhein-Westfalen e.V., "Salary Schedule 2010/2012 (ERA)," page 6, "Point System for Evaluating Job Functions" https://metall.nrw/fileadmin/_migrated/content_uploads/Tarifkarte_ERA_2010-2012_englisch_01.pdf (accessed May 22, 2019)

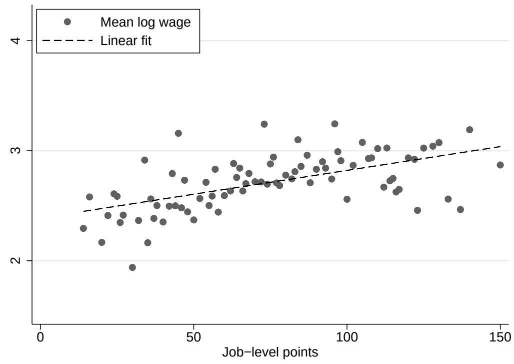
job-leveling system is from 10 to 170 points. For the skills part, we assign 10 points if a quick briefing is sufficient and no vocational training is necessary to execute the tasks and duties of the worker's current job. We assign 30 points if a longer working-in period is required but still no vocational training, 50 points if the job requires apprenticeship training, 80 points if the job needs a master craftsperson or technician certificate, and 100 points if the job requires a university or technical college degree. We further assign 6 points if the job involves complex/qualified tasks and 12 points if it involves highly complex/qualified tasks. For autonomy, we assign 2 points if the same work cycle is repeated in detail often, 10 points if this is sometimes the case, and 18 points if this is rarely the case. For jobs where the same activity is never repeated, we assign 30 points if it is a complex/qualified job and 40 points if it is a highly complex/qualified job. For communication and cooperation, we assign 2 points if the job requires no communication with other people, 4 points if this is sometimes the case, and 10 points if this is often the case but the job rarely or never requires improving on existing procedures or trying something new. We assign 15 points if the job requires communicating often and sometimes requires improving on existing procedures, and we assign 20 points if it is often the case that the job requires improving on existing procedures or trying something new. Finally for responsibility, we assign 10 points if the job includes supervisory duties and 10 additional points if the job involves supervising more than 20 other workers. We sum these job-level points to the total job-level points for each observation in the data.

C.2 Results for blue-collar workers

Section 4 discusses job leveling using a combination of survey questions and answers from the BIBB/BAuA 2012 survey and the job leveling scheme from the union bargaining agreement for steel and metal workers in North-Rhine-Westphalia. We explain the details of the implementation in Section C.1 of this appendix. We report results for white-collar workers in Figure 8 in the main text; Figure 24 reports corresponding results for blue-collar workers. We report separate results for white- and blue-collar workers because of different job complexity variables. After implementing the job-leveling scheme for blue-collar workers, we find again an increasing relationship between job-level points and wages (Figure 24). There are fewer blue-collar workers in the data, so estimates are less precise. The linear fit to average wages by job-level points accounts for 33% of the cross-sectional wage variation in Figure 24.

Figure 25 visualizes the distribution of wages for each job-level point (in groups of 5 points each), the data we have used to construct Figures 8 and 24. We find variation in wages at each point level, but the variation across job levels clearly dominates the

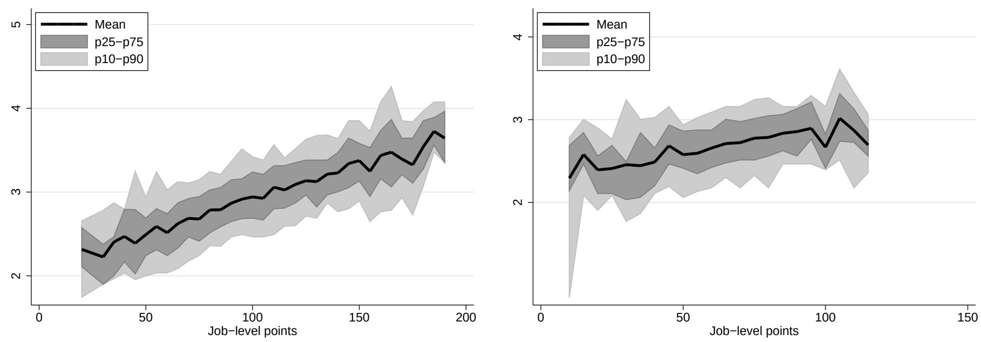
Figure 24: Average wages by job-level points (blue-collar workers)



Notes: Average (log) wages by job-level points. Job-level points have been constructed from survey questions on job characteristics (see text in Section 4 for details). Each dot represents the average log wage for the job level points. The dashed line shows the linear fit.

variation within job levels. For blue-collar workers,the variation across job-level points is somewhat smaller, but there is still a clearly positive relation between wages and job-level points.

Figure 25: Distribution of wages by job-level points



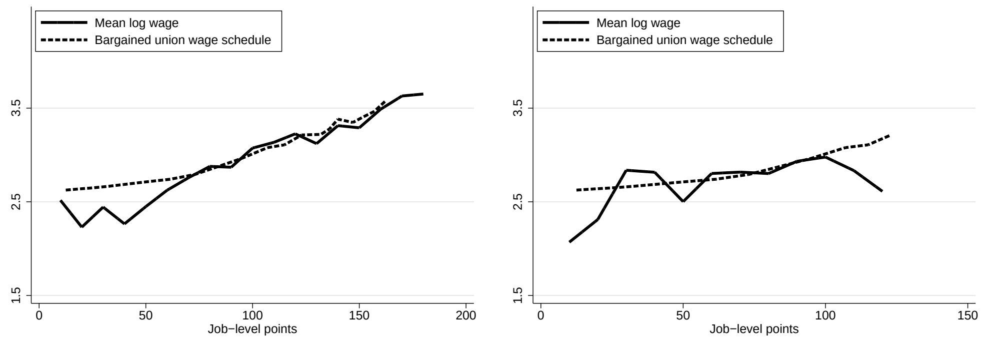
(a) White-collar workers

(b) Blue-collar workers

Notes: Average (log) wages by job-level points (in groups of 5 points) and the 10/25/75/90 percentiles within each group. The left panel shows white-collar workers, the right panel blue-collar workers. Job-level points have been constructed from survey questions on job characteristics (see text in Section 4 for details).

Finally, we explore how well our implementation of the point-leveling scheme aligns with reported wages from the union bargaining contract. For this, we focus on workers from North-Rhine-Westphalia in the BIBB/BAuA data and compare their average wages by point level to the reported wages by job level from the union bargaining agreement for steel and metal workers. Figure 26 shows wages from the BIBB/BAuA data by point level together with wages taken from the union bargaining agreement. Overall, we find a good fit between wages by job levels from the microdata in comparison to the wages from the union bargaining agreement. The BIBB/BAuA data are for 2012 and also include workers not covered by a union bargaining contract and not working in the steel and metal industry. The data for wages from the union bargaining contract are for 2018 and have been adjusted for inflation and average real wage growth. The close fit suggests that our implementation based on the selected survey questions provides a close approximation to how base wages of workers are set in practice.

Figure 26: Average and bargained wages by job-level points for North-Rhine-Westphalia (blue-collar workers)



(a) White-collar workers (b) Blue-collar workers

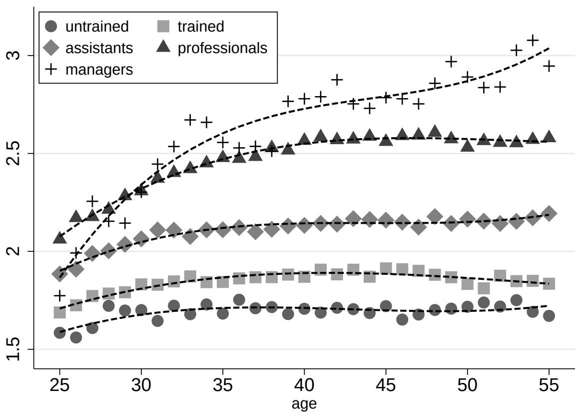
Notes: Average (log) wages by job-level points and bargained wages for steel and metal workers. Workers in BIBB/BAuA data from Nord-Rhine-Westphalia. Bargained wages for steel and metal workers for North-Rhine-Westphalia for 2018 have been adjusted to 2012 euros for CPI and average real wage growth. Job-level points have been constructed from survey questions on job characteristics (see text in Section 4 for details). The lines represent the average log wage for the job-level points (in groups of 5 points).

D Socio-Economic Panel (SOEP) data

Section 5 uses panel data from the German Socio-Economic Panel (SOEP) to explore the relationship between career progression and labor market mobility. The SOEP data are equivalent to the U.S. Panel Study of Income Dynamics (PSID) data. The data cover the period from 1984 to 2015. This section provides additional information on wages, job levels, and career progression of males and females from the SOEP data.

First, we consider wage differences by job level over the life cycle. Figure 27 shows (log) wages by job level from the SOEP data corresponding to the results in Figure 1 based on SES data. Job levels are not directly comparable because of different coding approaches (see Section 5.3). Wage differences over the life cycle, however, show patterns similar to the SES data, in particular for the four lower job levels.[29] There is roughly an 80 log point difference between average wages in untrained jobs and professional jobs and a 40 log point difference between the untrained job level and the assistant job level. A key difference that is related to the different coding approaches is the strong increase in wages for managers in the first part of the working life. This finding reflects that compared to the SES data, the SOEP job-level data have a smaller top group with less mobility between groups.

Figure 27: Wage by age and job level (SOEP)



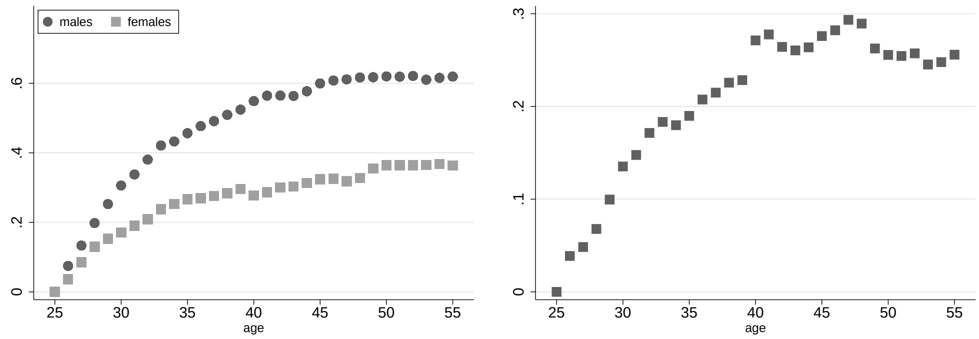
Notes: Mean (log) real wage by age and job levels from SOEP data (1990-2015). Year fixed effects have been removed. The job-level information is not directly comparable to the SES job levels. See text for details.

Figure 28 complements the findings from Figure 4(a) in the main part of the paper. In Figure 4(a), we document the differences in the job-level component for males and females by age and observe a widening around age 30 when female careers slow down considerably. Figure 28 uses the information on promotions and demotions from the SOEP data discussed in Section 5. We exploit the panel dimension of the data to accumulate promotions and demotions at the individual level. We summarize the life cycle promotion dynamics by net promotions where we sum over all promotions up to a certain age and subtract all demotions. Figure 28(a) shows accumulated net promotion profiles for males and females. The vertical axis shows the average net promotion, so that a number of 0.5 means that up to this age, every second worker moved up one job level on net. For males, we find cumulative net promotions of 0.6 at age 55 and for females less than 0.4 net promotions. The net promotion profiles trace the dynamics of the job-level components from Figure 4(a) in the main part of the paper, in particular, we observe a strong slowdown of promotion dynamics for females after age 30. Figure 28(b) shows the difference in net promotions for males and females. Unlike for the job-level component from Figure 4(a),

[29]Because of missing hours information, we construct wage data only from 1990 onward.

we already see a widening of promotion dynamics at age 25 that continues up to age 40 when the difference in net promotion stabilizes at about 0.25. This implies that every fourth net promotion for males is not taking place for females and that this difference arises in the first half of the working life. However, one should also take into account that the SES data and the SOEP data cover different survey years.

Figure 28: Cumulated net promotions and demotions by age



(a) Cumulated net promotions (b) Differential cumulated net promotions

Notes: The figures display the accumulated net promotion rates for male and female workers from the SOEP data (1984-2015) and their differences across gender by age.