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Which Ladder to Climb?
Wages of workers by job, plant, and education*

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Abstract

Wages grow but also become more unequal as workers age. Using German administrative data, we largely attribute both life-cycle facts to one driving force: some workers progress in hierarchy to jobs with more responsibility, complexity, and independence. In short, they climb the career ladder. Climbing the career ladder explains 50% of wage growth and virtually all of rising wage dispersion. The increasing gender wage gap by age parallels a rising hierarchy gap. Our findings suggest that wage dynamics are shaped by the organization of production, which itself likely depends on technology, the skill set of the workforce, and labor market institutions.

Keywords: human capital, life-cycle wage growth, wage inequality, careers
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1 Introduction

Wages grow but also become more unequal as workers age. Assumptions on the drivers of these life-cycle wage dynamics are key inputs to models in human capital theory, models of labor market dynamics, and heterogeneous agent incomplete market models. Differences in employers, in educational attainment, or in the jobs workers perform are all potential drivers of the observed wage growth and rising wage inequality — but what is their relative importance in explaining the facts? This paper relies on largely unexplored German administrative data to decompose life-cycle wage dynamics and to provide an answer to this question.

The answer we provide is strong: we largely attribute both life-cycle facts to a single driving force: the life-cycle changes in the hierarchy levels of jobs. The hierarchy level of a job describes the responsibility, complexity, and independence in the organization of the work flow associated with that job. Over the life cycle, some workers climb the career ladder and progress into jobs higher up in the hierarchy dimension. We find that climbing the career ladder explains 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. We demonstrate that the rising gender wage gap by age parallels a rising hierarchy gap. Exploring the determinants of career progression, we find a non-monotone effect of education, with steeper career paths at the top and bottom of the distribution. We also provide evidence for the presence of luck in career progression. The finding on the importance of hierarchies makes organizational structure of plants key for wage dynamics.

The data we explore are three waves of administrative linked employer-employee data representative of the German economy. We apply synthetic panel regressions to control for unobserved heterogeneity (Deaton, 1985; Verbeek, 2008) and to identify the causal effect of job and worker characteristics on wages. Using the estimated effects, we quantify how much changes in observable characteristics contribute to wage growth and wage dispersion. We group observable characteristics following human capital theory based on their specificity into three drivers of wage dynamics: first, an *individual component* that does not change by changing jobs or employers; second, a *plant component* that will only change with a change in employer; and third, a *job component* that can change over the career of a worker even at the same employer.

Using this decomposition approach, we find that differences across plants shape wage dispersion at labor market entry. Yet, it is the job component, in particular a job's complexity, responsibility, and independence, summarized in the hierarchy level of a job, that explains 50% of wage growth and almost all of the rising wage dispersion over the

working life, because wage differences across hierarchies are large. For example, climbing the career ladder from the lowest to the highest level of hierarchy leads to more than a tripling of wages. Consequently, differences in progression on the career ladder lead to substantial wage differences.

Vice versa, we show that the development of life-cycle gender wage differences is strongly related to differences in career progression. At the beginning of their careers, females have roughly 7% lower hourly wages than males (across all firms and jobs); at the end of their careers that difference is more than 30%. Half of this widening gap is explained by the fact that female career progression drastically slows down around the age of 30, while males continue to climb the career ladder until age 50. Males and females also differ in the importance of employer differences for wage growth. While 20% of male wage growth over the working life comes from moves to better-paying employers (controlling for worker and job characteristics), females start to move to worse-paying employers after the age of 30. This and the lack of career progression of females are likely interrelated because not all employers have the same organizational structure. Well-paying employers also offer on average more jobs at higher levels of hierarchy.

Exploring the determinants of career progression, we find that education is positively correlated with higher ranks in the hierarchy. We also find steeper slopes of career profiles for workers without vocational training (both workers with only a secondary education and workers with a college education). To explore the role of luck in career progression, we take the ranking of a worker in terms of experience relative to a peer group of coworkers within the plant as being beyond the worker's control and, hence, a source of luck. We find a statistically and economically significant *silverback effect* — workers higher up in the experience distribution of peers are also found further up on the career ladder. We interpret the presence of this silverback effect as evidence for luck in career progression.

Our database is three waves of the German Survey of Earnings Structure, large administrative samples that offer linked employer-employee micro data representative for the universe of employees and employers, working at plants with at least 10 employees. The database contains roughly 6 million employee and 100,000 plant observations across survey years. An important feature of the data is that they are directly obtained from plants' human resources departments. Measurement error on all characteristics can therefore be expected to be particularly low. The data report the actual (virtually uncensored) pay and hours worked of employees. They include detailed information on workers' education, occupation, age, and tenure. In addition, they provide a description of the complexity, responsibility, and independence of an employee's job, coded as five levels of *hierarchy*. Taken together, all information on jobs, employers, and workers explains over 80% of the observed cross-sectional variation in wages, whereas cross-sectional wage regressions in

other data sources mostly explain one-third of wage dispersion by observables.[1] Detailed information both on employers and on the hierarchy levels of jobs is equally important for explaining the cross-sectional variation, but even when used as the single and only explanatory factor, five hierarchy levels explain more than 45% of wage variation.

Our analysis also speaks to the importance of worker mobility across plants for the evolution of wage growth and wage inequality over the life-cycle, i.e., for the job ladder. The job ladder can be climbed in two ways: by improving your position in the hierarchy or by moving to a plant that pays better overall. Note that both may happen simultaneously. We find that taking into account hierarchy information diminishes the importance of fixed plant differences as a determinant for wage growth and the growth of wage dispersion. Plant differences and job ladder dynamics feature prominently in search models of the labor market. We highlight a new channel through which plants and mobility across them are important because jobs of different levels of hierarchy are not evenly distributed across plants. Differences in organizational structure across plants correlate with plants' average pay. In general, plants paying well on all levels of hierarchy also offer more jobs with high levels of responsibility and independent decision making.[2] Such employer differences in the organizational structure determine the opportunities for career progression and provide a new motive for labor market mobility across employers.

Our analysis is based on representative data for the German labor market but we also provide evidence that these findings generalize beyond the German case and likely apply to most labor markets in industrialized countries. Our evidence is based on high-quality data from the National Compensation Survey (NCS), a representative employer survey for the United States. The NCS data contain job-level information that matches closely the hierarchy information in our data. We demonstrate that, in line with the evidence for the German labor market, job levels in the NCS data explain a large part of wage variation in the cross-section and even within occupational groups. Our literature section below cites further evidence to support this conclusion.

The finding that climbing the career ladder is the key driver of wage growth and increasing wage dispersion during the working life provides new insights for the strands of economic research that explore the drivers of secular trends in the wage structure, the consequences of search frictions in the labor market, or the literature that explores

[1] Although this is a 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). Alternative approaches that use panel estimation with two-way fixed effects based on the approach in Abowd et al. (1999) also achieve such levels of explanatory power.

[2] In fact, when job characteristics are ignored, plants appear to be more important in explaining both average wage increases and the life-cycle profile of inequality. In other words, high-paying plants are high-paying because of their job composition rather than some other intrinsic characteristics of the plant.

the consequences of wage risk for consumption-saving decisions. One interpretation of our finding is that wage dynamics are shaped by the organization of production within plants. This organizational structure may itself depend on technology, the skill set of the workforce, and labor market institutions, as, for example, in Acemoglu (2003). This view implies that policy or macroeconomic changes like increasing automation, rising college attainment, or reforms of the old-age pension system that induce firms to change their organization of production will also affect the life-cycle wage dynamics of workers.

It seems complicated to reconcile with search models of the labor market that assume that jobs are drawn from a fixed distribution of job types without rivalry in the availability of jobs. Our results suggest that rivalry in jobs is important so that staffing and promotions are more like playing musical chairs where filled jobs become unavailable to other workers. At the same time, these externalities offer a new motive for labor market search and mobility because career opportunities differ across employers depending on their organizational structure. The results further point to strong job specificity of productivity that is determined by the organizational structure of an employer. This implies that when an employer-worker match resolves, a high-paying (highly productive) job persists for the employer and is only lost from the worker's perspective.

Relevant for macroeconomic heterogeneous agent models are the implications for the determinants of wage risk. Our results suggest that how workers move along the organizational structure is a key determinant of wage risk, and furthermore, that life-cycle wage growth and wage risk are linked because both result from the same underlying process of career progression. This view scrutinizes the widely maintained assumption of the exogeneity of wage dynamics to changes in the macroeconomic environment like technological progress, demographic change , or policy reforms. In addition, the fact that we are able to identify determinants of career progression suggests that workers might know already at labor market entry that their wage dynamics differ from those of other workers. Hence, wage dynamics are heterogeneous. Differences in future wage dynamics translate —through the lens of these models— into differences in savings choices right from the start.

The remainder of the paper is organized as follows: Next, we put our results into perspective by reviewing the related literature. Section 2 then introduces the data set on which our analysis is based. Section 3 reports the results on the decomposition of wage growth and rising wage inequality. Section 4 discusses the determinants of career progression. Section 5 provides a sensitivity analysis for our key findings, evidence that hierarchy levels are also a major determinant of the US wage structure, and discusses the role of job composition across plants. Section 6 concludes. An appendix follows.

1.1 Related literature

Our paper focuses on exploring the sources of wage growth and inequality over the life cycle. In doing so, we pick up a long-standing economic research agenda, going back at least to the seminal work of Mincer (1974), that has evolved in a large literature documenting a variety of patterns of life-cycle wage growth and inequality, for example, Deaton and Paxson (1994), Storesletten et al. (2004), Heathcote et al. (2005), and Huggett et al. (2006). One part of this literature interpreted the residuals from Mincer-style wage regressions as wage risk and estimated stochastic processes to describe this risk. Examples are Lillard and Willis (1978), MaCurdy (1982), Carroll and Samwick (1997), Meghir and Pistaferri (2004), and Guvenen (2009). These estimated risk processes have become a key building block of macroeconomic models with heterogeneous agents. Recently, Huggett et al. (2011) and Guvenen and Smith (2014) took more structural approaches to explore the drivers of life-cycle inequality. A defining feature of all of these papers is that rising life-cycle inequality results mainly from an unfolding stochastic process with persistent idiosyncratic shocks. We add to this literature by relating this stochastic process to observables, in particular, steps on the career ladder and differences between employers. The latter relates our work to Low et al. (2010), Hornstein et al. (2011), and Jung and Kuhn (2016), who explore employer differences as a source of wage inequality in the context of search models.

Employer differences also feature prominently in a different strand of the literature that investigates the sources of rising wage inequality over time. Card et al. (2013) provide a particularly relevant example as they look at the case of Germany. They apply the approach developed by Abowd et al. (1999) to four time intervals of German social security data covering the period from 1985 to 2009. While rising worker differences and the covariance with firms are most important in explaining rising wage inequality, rising firm differences are also a significant contributor. Song et al. (2015) construct an impressive new data set from social security records in the United States to study rising earnings inequality for the period from 1980 to 2015. They also apply the approach by Abowd et al. (1999) to different time intervals and find that between-firm differences are the important driver of rising earnings inequality. Song et al. (2015) and Card et al. (2013) both argue that changes in the organizational structure of firms are likely the driver of rising between-firm pay differentials. This explanation would be in line with recent evidence for Germany in Goldschmidt and Schmieder (2017), who document the importance of organizational changes from domestic outsourcing for wage changes, especially in the lower part of the wage distribution.

Our findings also echo the literature on internal labor markets and career dynamics within firms. Our analysis differs in two important dimensions from the existing studies. First

in focus, we look at the importance that hierarchies and employers have for wage growth and the increase in inequality over the life cycle. Second in scale, we explore representative data for the entire labor market, while the existing literature considered case studies of single firms and sometimes even subgroups of workers within these firms. Baker et al. (1994) provide one of these fascinating case studies on hierarchies, careers, and internal labor markets. They document large wage differences across hierarchy levels, and they show that few hierarchy levels —six in their case— suffice to represent the organizational structure of the firm and that five hierarchy dummies explain 70% of the wage variation within this single firm. They find further that, absent promotions across hierarchy levels, there is virtually no individual wage growth for workers over time. There are two important takeaways from their work for what we do. First, hierarchies should be interpreted as one simple way to represent the more complex organizational structure of firms. Second, they provide evidence contradicting the idea of reverse causality from wages to hierarchies in the sense that hierarchies are determined based on wage levels. Dohmen et al. (2004) provide another fascinating case study on the aircraft manufacturer Fokker that corroborates the key findings from Baker et al. (1994) relevant for our analysis. Again, they provide evidence for the fact that hierarchies determine the wage structure rather than the reverse. Gibbs et al. (2003) and Fox (2009) both document for Swedish matched employer-employee data —similar to what we find— that promotions along the hierarchy ladder are key or even the most important source of earnings growth.

For theoretical models in this strand of the literature, Waldman et al. (2012) provide an excellent overview. At the center of his discussion are the seminal papers by Lazear and Rosen (1981) explaining promotion dynamics as a result of tournaments and by Waldman (1984) emphasizing the signaling role of promotions in an environment with asymmetric information about worker ability. Lazear and Rosen's work (1981) is of particular interest for our analysis because they provide a theory as to why rank-order wage schemes exist in firms, i.e., wage schemes where wages do not depend on a worker's output but on the worker's hierarchy level in the firm. 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 hierarchies into the production process and a relative shift of the worker-skill to the production-task ("problem") distribution can then explain rising wage inequality of the magnitude observed in the data. Importantly, the change in wage inequality in the model results from the endogenously changing organizational structure. Reduced-form empirical models like that of Abowd et al. (1999) would likely pick this up by changing firm fixed effects and their covariance with worker effects. Closely related is

the paper by Caliendo et al. (2015), who study a sample of French manufacturing firms. They find that an organizational structure with four layers of hierarchy explains up to 66% of within-firm wage variation. They provide empirical support for the theoretical model in Garicano and Rossi-Hansberg (2006) by exploring the dynamic evolution of hierarchies and wage structures when firms grow and shrink. In our analysis, we will also explore the link between organizational structure and firm wage differentials in detail. One difference with the existing literature is that we explore the life-cycle dimension of careers in terms of hierarchy.

2 Data

We use data from the 2006, 2010, and 2014 waves of the Survey of Earnings Structure ("Verdienststrukturerhebung"), henceforth SES, for our analysis. The SES data are an administrative representative survey of establishments (short: 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 non-response 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 worked, both regular and overtime, are extracted from the payroll accounting and personnel master data of establishments and directly transmitted via a software interface to the statistical office. Transmission error is therefore negligible.
The data cover public and private employers in the manufacturing and service sectors. Self-employed workers are not covered. In 2006, the survey has information on roughly 28,700 establishments with about 3.2 million employees, 1.9 million employees from 32,200 establishments in 2010, and 0.9 million employees from 35,800 plants in 2014. The data are representative of 21 million workers in Germany.

2.1 Sample selection and variable definition

For our baseline analysis, we restrict the data to workers whose age is 25 to 55. After having estimated the effect of observables, we split the sample by males and females when analyzing the life cycle because male and female career paths differ substantially, as we will show. We drop very few observations where earnings are censored,[3] and all

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

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 hierarchy information. Since we use plant fixed effects, we also 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 overtime hours. In our regression analysis, we use controls for experience, education, sex, occupation, and hierarchy. We construct experience as potential experience starting at age 25. Sex is naturally coded. For education, we consider four groups: workers with a secondary education but without vocational training, workers with vocational training, and workers with a college education. The fourth group are workers for whom education is not reported or with other levels of education. Importantly, this includes workers who have not completed a secondary education.[5] For convenience, we will refer to the education level of this fourth group as *other* for the remainder of the analysis. For occupation coding we use 2-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 describe the hierarchy variable in detail next.

2.2 Job complexity, responsibility, and independence: The hierarchy variable

Importantly and different from many other data sources, our data distinguish among five levels of hierarchy in describing the job of a worker. These hierarchy levels are defined based on the complexity of a job (skill and typical educational requirements), the responsibility (for one's own work or the work of others), and the independence (the decision-making power and discretion in the work flow) associated with a job.[7] The lowest hierarchy level is workers who perform simple tasks (*untrained workers, UT*). The tasks for these workers typically do not require particular training (such as an apprenticeship) and can be learned on the job in less than 3 months. The second level (*trained workers, TR*) covers tasks that require some occupational experience but no full occupa-

[4]For a large set of observations this information is missing. The information is only available if in a region-industry cell there are at least 3 firms in which the state has a major influence. Major influence is defined as being a government agency, the state owning 50+ % share, or due to 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 data sets. It that shows that all workers without a completed secondary education are coded in our education variable as the "other" group.

[6]Crosswalk retrieved from http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm.

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

tional training (apprenticeship). Tasks performed at this hierarchy level can be typically learned on the job in less than 2 years. Workers at the two lowest hierarchy levels do not undertake any decisions independently and have clearly defined work flows. Only from the third level of hierarchy onward do employees have some discretion regarding their work. Jobs at the third hierarchy level (*assistants, AS*) typically require a particular occupational training (apprenticeship) and in addition occupational experience. Workers at this level prepare decisions or take decisions within narrowly defined parameters. An example would be a tradesman, junior clerk, or salesman. These workers usually decide on everyday business transactions (e.g., a sale) and thus have some discretion. Yet, they are neither responsible for the work of others nor do they decide on tactics or strategy of the business. The fourth hierarchy group works on tasks that typically require both specialized (academic or occupational) training and experience (*professionals, PR*). Importantly, they perform their tasks independently, they have substantial decision-making power over their cases/transactions/organization of the work flow, and they have some decision-making power in regard to the work of others. Typically, these workers oversee small teams (examples would be foremen in production, junior lawyers, heads of office in administration). The fifth hierarchy level is managers and supervisors (*management, MA*). Their primary task is strategic decision making, which requires high levels of independence and comes with substantial responsibility regarding the work of others.
Importantly, hierarchy is neither an educational nor an occupational concept, though both are related to hierarchy. We document in Appendix A that each education group is represented significantly in at least three hierarchy levels and the typical 2-digit occupation in our sample spans three hierarchy levels. Appendix A also provides further detailed information on the definition of the hierarchy variable. We discuss the role of education for career progression along the hierarchy dimension in Section 4. As discussed in section 1.1 above, hierarchies describe the organizational structure within a plant and are independent of the wage structure as has been shown in existing case studies and is also emphasized in the documentation of relevant data documentations for our data but also the National Compensation Survey for the United States.

2.3 Descriptive analysis

Table 1 reports the number of observations for each 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 €17.5 in 2010 for males but returned to €18.3 in 2014. Female median real wages have fallen from €14.7 to €14.4 between 2006 and 2010 and

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

	Wages (in 2010 €)					Pop. Share of Hierarchy (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

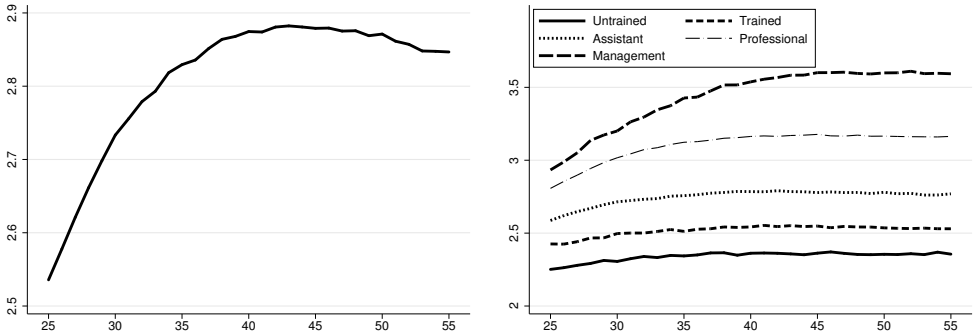
Notes: "Wages" refers to the hourly wages in constant 2010 prices. "Av." is the average and "p10/50/90" are the 10/50/90 percentile of the wage distribution, respectively. "Pop. Share of Hierarchy" refers to the population share of a hierarchy level in the sample population, where "UT/TR/AS/PR/MA" are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

then grown again to €14.9. 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.

In addition, Table 1 reports the population shares of workers at the five different levels of hierarchy. The share of male workers (values for females in parenthesis) with high or very high independence 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 who have autonomy only within very clearly defined limits, i.e., only in how they carry out a given task or with respect to the substance of the question they need to decide (AS), has increased from 43.4% (46.2%) to 45.9% (51.4%) (females in parenthesis), while the share of male (female) workers that have no autonomy at all (TR+UT) went down from 22.8% (31.4%) to 19.1% (24.7%).

In the data, the average wage of an employee increases substantially during the working life. The average wage of a worker increases by roughly 2% with every year of age between age 25 and age 45 and levels off afterward (Figure 1(a)). Yet, this average wage increase masks substantial heterogeneity. Figure 1(b) reports the mean log wage by age

Figure 1: Wage by age and hierarchy level



(a) All workers

(b) Workers by hierarchy

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 hierarchy levels. Year fixed effects have been removed.

conditioning on hierarchy levels. We find that the top hierarchy group (Management) always has the highest wage and sees the strongest increase in wages with age, so that the wage differences between the top level and the other groups widen with age. For example, a worker constantly remaining at the *assistant* hierarchy level will have less than a 20 log-point increase (22%) in his/her wage over his/her lifetime, roughly half the average wage increase, while at the management level, wages rise by more than 60 log points (82%), roughly twice the average increase. A worker climbing up the career ladder from a job as an untrained worker to a management-level job will see a stellar 140 log-point increase (306%) in his/her wage over his/her lifetime. These descriptive statistics suggest that moving up the career ladder is likely 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 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 can explain more than 81% of wage variation in the cross-section if we use plant fixed effects. Even without plant fixed effects but with plant-level controls, 62% of wage variation in the cross-section can be explained; see Table 6 in Appendix A.2. Part of this high explanatory power is due to the high quality of the data. A second part comes from the fact that the data contain information about hierarchy levels of jobs. Using only hierarchy dummies explains 46% of the cross-sectional wage variation in our sample.

3 The life cycle of wage growth and wage inequality

To understand the factors that contribute to wage growth and wage inequality over the life cycle, we estimate the effect of various plant, job, and worker characteristics on wages. We deal with the challenge of unobserved heterogeneity by using synthetic panel methods. A simple OLS estimator of, for example, the impact of a job's hierarchy levels on wages might be inflated because more able workers obtain higher wages at any job and are also more likely to end up on higher hierarchy levels. The synthetic panel methods exploit the fact that aggregation of the micro data to a cohort level creates a panel structure (see Deaton, 1985; Verbeek, 2008, for an overview of the method).[8]

3.1 Methodology

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

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

where J_{ipt} is the characteristics of the job of the individual, I_{ipt} is the characteristics of the individual itself, γ_i is the worker fixed effect, and ζ_{pt} is the effect of plant p at time t. This means that $\beta_I I_{ipt}$ captures the wage effect of worker characteristics that can change without changing jobs or plants, the *individual component*. Specifically, we use education and gender-specific age dummies.[9] The *job component*, $\beta_J J_{ipt}$, captures the characteristics of a job that can change without changing plants. Here, we use dummies for two-digit occupations and dummies for the hierarchy level of a job.
To control for plant effects, we first demean all variables at the plant level

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

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. Thereafter, to control for individual-specific fixed effects, we construct synthetic cohorts for the panel regression. We define cohorts based on workers' sex, birth year, and regional information (North-South-East-West).[10]

[8] Appendix C.2 considers a case without controlling for individual fixed effects.

[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% p.a.; see Wanderungsstatistik of the Statistisches Bundesamt. More than a third of this migration is between states of the same region.

We aggregate the variables to the cohort level and obtain

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

where $\hat{\bar{X}}_{ct}$ denotes the average of $\hat{X}_{it}$ within a cohort c. We finally use this equation to obtain estimates $\tilde{\beta}_J$ and $\tilde{\beta}_I$ by fixed-effects OLS. The minimum observations across cohort-year cells is 415, the maximum is 8383, and the median is 3461. Since we do not observe any cohort over its entire life cycle, the identifying assumption is that the life cycle is stable across cohorts.[11]

We use the estimated coefficients to construct the plant component. The plant component is the observed average wage at the plant minus the average individual and job component at the plant. It is given by

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

This means that our estimated plant component, ζ_{pt}, corrects the average wage at a plant for differences in organizational structure and workforce quality by removing the average individual and job components across plants.[12]

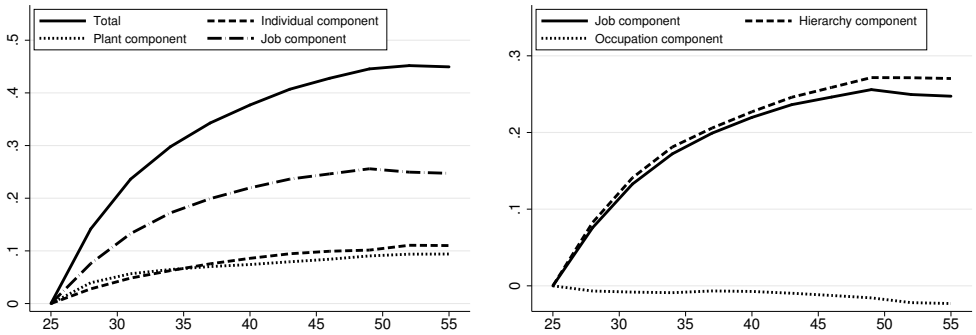
3.2 Wage growth

The estimated individual, job, and plant components allow us to decompose mean wages over the life cycle. We calculate the average wage and the three components for all workers in an age-year cell and then regress these averages on a full set of cohort and age dummies. We report the coefficients on the age dummies as our life-cycle profiles, always normalizing the log wage of a 25-year-old to zero in the following figures. We decompose wage growth of male and female workers separately. The reason is that, as we will see, these decompositions show very distinct patterns because males and females have different career paths. We first look at males, discuss female workers in the second step, and compare career paths in a third step.

[11] This assumption has to be taken into account when interpreting our results. Male (female) workers of younger cohorts work more (less) part-time and are less (more) likely to participate in the labor market than a generation before.

[12] This implies that the plant component estimate will capture the average *unobserved* heterogeneity of workers within a plant, too. 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 log wage difference. Right panel: Decomposition of the job component (solid line) into the contribution of occupations (dotted) and hierarchies (dashed). The 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 3-year groups).

3.2.1 Males

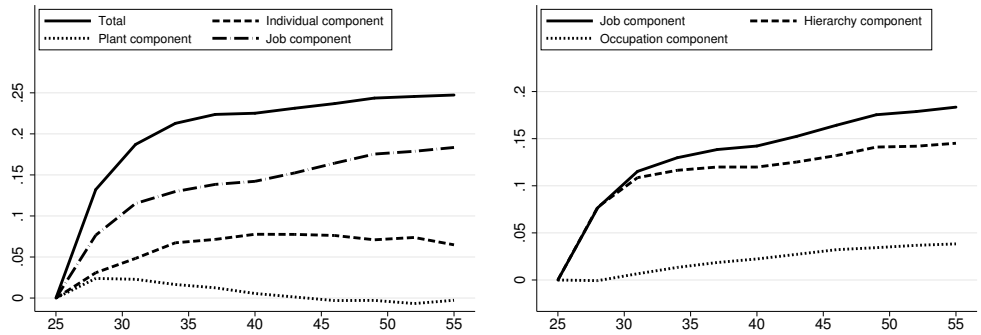
Our first set of results regards average wage growth for males. Figure 2(a) reports the decomposition of mean log wages into its components. On average, the wages of men grow by approximately 45 log points over the life cycle.[13] The job component alone explains more than 50% and up to 58% of wage growth by age. Moving to better-paying plants over the life cycle, climbing the job ladder, contributes approximately 20% to wage growth. The remainder, the individual component, captures a pure experience effect.
Within the job component, it is promotions along the hierarchy dimension that are key to explaining average wage growth, as Figure 2(b) shows. In fact, movements across occupations contribute slightly negatively to wage growth, controlling for hierarchy levels. In turn, most of the life-cycle wage growth results from workers taking on jobs with increasing degrees of responsibility, complexity, and independence over the course of their careers. We explore the relation between tenure with the same employer and education and steps on the career ladder in Section 4.

3.2.2 Females

Female and male labor market performance is known to differ along many dimensions. Average wages of females are lower and grow less over the life cycle. Our decomposition

[13]The difference in the descriptive analysis by age as in Figure 1 stems from cohort effects.

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

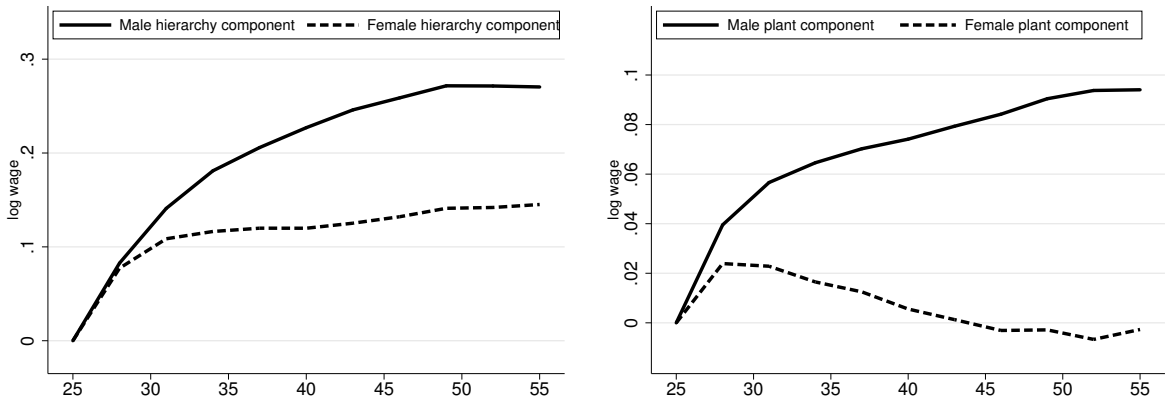
in Figure 3(a) shows that this difference is rooted in the smaller increase in the job component, in particular, the slower move up the career ladder for women. Female wages grow over the life cycle by only 25 log points, compared to 45 log points for males. The job component still accounts for the lion's 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 hierarchy component for females. It only starts to increase again slightly after age 45. A substantial part of the increase in the job component for females stems from the occupation component, which contributes almost 5 log points to the wage growth of females (Figure 3(b)), unlike for men, where it contributes if anything negatively. The individual component for females contributes in relative terms slightly more to total growth than for men (30% vs. 25%). Interestingly, the plant component shows a decreasing profile for females after age 30. One reason could be that the non-wage aspects of a plant, such as its location or working time arrangements, play more important roles for females than males at this stage of the life cycle. As we will show below, the plant component is correlated with the organizational structure of plants. Plants with a high plant component offer on average more jobs at the top of the hierarchy. 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. This is close to the estimate of the adjusted gender pay gap by the German Statistical Office but, as a raw

average, 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 important different careers along the hierarchy ladder are for the widening of the gender wage gap over the life cycle. It shows the hierarchy component from Figure 2 (males) and Figure 3 (females).

Figure 4: Hierarchy and plant component of males and females



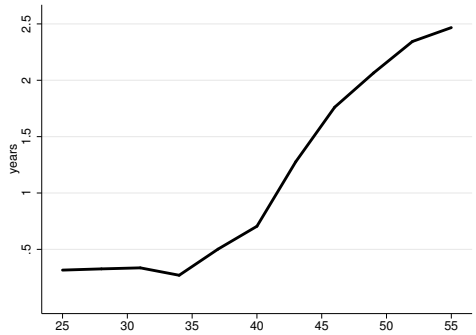
(a) Hierarchy component

(b) Plant component

Notes: (a) Hierarchy 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 hierarchy 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. The result is an increasing wage difference between males and females exceeding 10 log points at the age of 50. This is 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 comes from differences in mobility across plants. While males continuously move on average to plants that pay better, females after the age of 30 tend to sort into plants that pay worse; see Figure 4(b). The different labor mobility pattern of females also shows up in employer tenure by age. Figure 5 shows mean tenure by age for males and females after controlling for cohort effects. Until their mid-30s, males and females have only a small difference in employer tenure of about 4 months. This difference increases strongly and almost linearly afterward, and up to age 55, it has grown to almost 2.5 years. This highlights again the diverging pattern of males and females starting after the first 10 years in the labor market, whereby females seem to end up in lower levels of hierarchy, at worse-paying plants, and with less stable jobs.

Figure 5: Tenure difference between male and female workers



Notes: Difference in mean tenure of male and female workers by age. Cohort effects have been removed. Horizontal axis shows age and vertical axis tenure in years.

However, interpreting these results as life-cycle facts and extrapolating them to the expected life-cycle profiles for younger cohorts of women should be taken with a grain of salt. Our sample spans nine years and the estimated life-cycle pattern also comes from comparisons across cohorts.

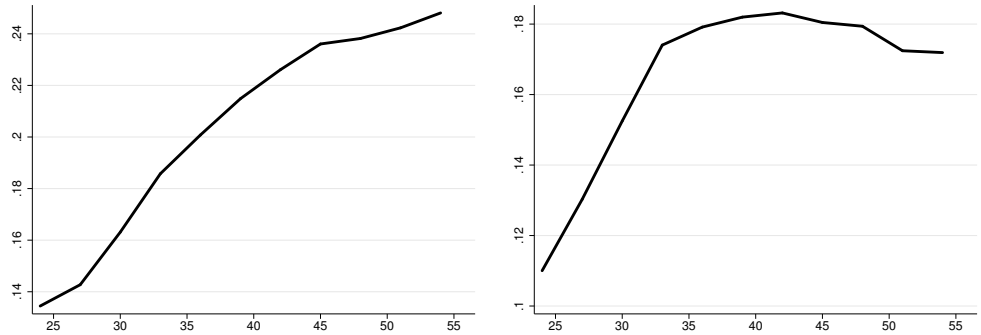
3.3 Wage inequality

While average wages grow, wage dispersion also increases substantially over the life cycle. Figure 6 shows the variance of log male and female wages 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 thirties and flat thereafter. This section uses the regression results from above to decompose the life-cycle increase in wage inequality. As for wage growth, we first discuss males, then females.

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 micro data based on cross-sectional regressions explain about 30% of the observed wage inequality by observables and leave the largest part of wage inequality unexplained. Consequently, the literature interprets the largest part of wage inequality and its increase with 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

Figure 6: Variance of log wages by age (raw data)



(a) males (b) females

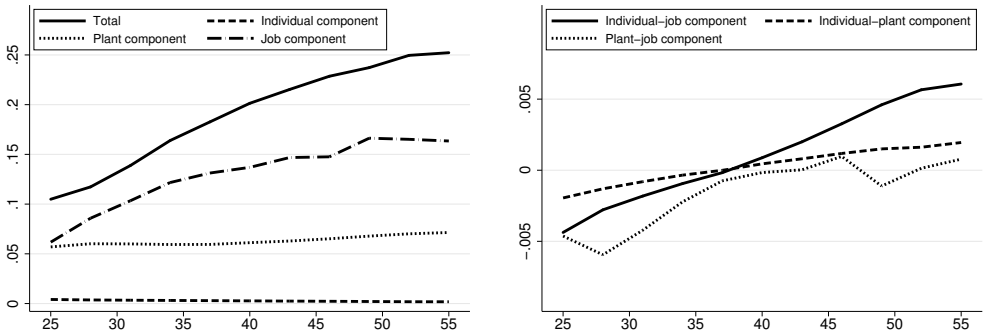
Notes: Variance of log wages for males and females. Left panel shows males. Right panel shows females. Horizontal axis shows age and vertical axis log wage variance.

behavior (see Heathcote et al., 2014, to give one example). The high degree of statistical determination in our data allows us to go beyond the scope of existing studies and shed new light on the determinants of wage inequality. We next explore the contribution of the job, individual, and plant components to rising wage dispersion over the life cycle.

In Figure 7(a) we display the life-cycle profile of wage dispersion controlling for cohort effects. Relative to the raw data in Figure 6, the profile becomes steeper. Over the life cycle, 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 coming from workers becoming increasingly different in the type of jobs they perform. As for average wages, the hierarchy level of the job is the main driving variable. The variance of the individual component is virtually zero. Education itself has a negligible direct effect on wage differences across workers. As we will show in Section 4, it has a strong indirect effect through promoting a worker's career.

There are two remaining components unreported in Figure 7(a): the variance of what is not explained and the sum of all covariance terms of observables. Figure 7(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 component and between the plant and job component increase over the life cycle. In words, young workers who are in high levels of hierarchy tend to be at low-paying plants and tend to have lower levels of education. When workers age, workers at high levels of hierarchy are found in

Figure 7: 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. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

all plants and are most likely to have high degrees of formal education.

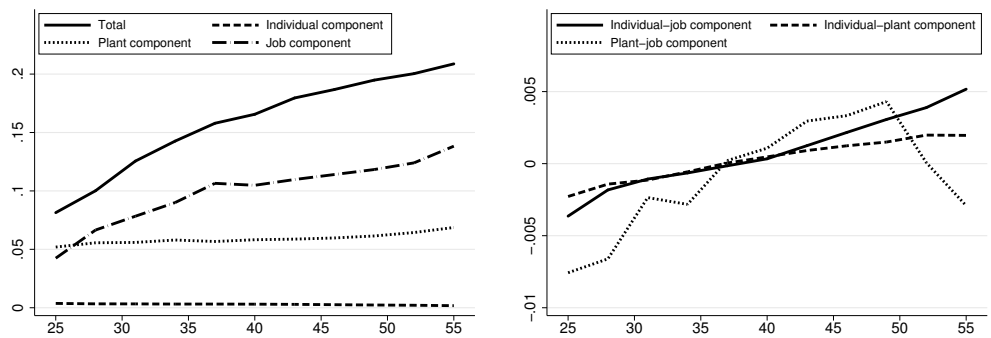
The sum over all covariance terms increases from slightly less than -1 log point to slightly less than 1 log point over the life cycle. This means that the covariance terms contribute another 4 log points to the increase of the variance over the life cycle (twice the difference between the two covariance terms). This is equal to the wage dispersion increase not explained by the job component alone. To summarize, the dispersion in the job component and the covariance of the job, plant, and individual components explain all of the increase in wage dispersion over the life cycle. This implies that the residual wage dispersion shows no life-cycle profile. The absence of any slope in the residual component suggests that we should draw strong conclusions about the source of rising wage inequality over the life cycle. A flat life-cycle profile is consistent with transitory i.i.d. wage shocks but it is clearly not consistent with a large persistent component in a stochastic process of residual wage risk over the life cycle.

3.3.2 Females

We have seen that women have a flatter hierarchy 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 8(a). In particular, the increase in hierarchy 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 explains over 2/3 of the 12 log-point increase in wage dispersion over the working life of females (compared to 15 log points increase in variance for males). For females, we also find a virtually flat life-cycle profile in the plant component. At the same time, the job-plant covariance profile is even steeper for women than for men. Those women who end up in high levels of hierarchy 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 at the age of 30. Plainly put, it seems that selection into careers is stronger for women than for men.

Figure 8: Variance-covariance decomposition (females)



(a) Variance (b) Covariance

Notes: Decomposition of the variance of wages of female workers; otherwise see Figure 7.

Our findings on the increase in wage dispersion over the life cycle point to career progression as the source of large and persistent wage shocks. Taken together with the results for life-cycle wage growth, this implies that wage growth and rising wage dispersion over the life cycle are tightly linked as they result from the same underlying dynamics on the career ladder. Identifying the underlying structure of wage dynamics is key for analyses that study the consequences of macroeconomic changes like technological change or policy reforms. Wage dynamics over the life cycle are a key ingredient to the employed structural models. These studies typically take wage dynamics as exogenous; our results scrutinize the general validity of such an exogeneity assumption.

4 Determinants of careers

By decomposing wage growth and wage dispersion over the life cycle, 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.

4.1 Role of human capital investment

There is a wide variety of channels how workers invest in their human capital. We consider the three most commonly considered channels for human capital investment: education, experience, and labor market mobility. Education in school or college is probably the most common form of human capital investment. Learning by doing 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 we investigate is the search for an employer providing a good match to the worker and offering career opportunities.

Table 2 provides a descriptive analysis of the relationship between education, experience, and the career ladder. We report by age groups the shares of workers on different hierarchy levels conditioning also on workers' educational attainment. We look at a younger age group with workers age 25 to 35 and an older age group with workers age 35 to 45. We further separate male and female workers. This simple descriptive statistic offers four interesting results. First, education and hierarchy are different. We find for all age groups and males and females that each education group has significant shares of workers across at least three levels of hierarchy. Second, education is positively correlated with hierarchy. Workers with higher levels of education are found further up in the ranks of hierarchy. Typically, 60% or more of workers with secondary education are on the two lowest hierarchy levels (UT+TR), while for workers with a college education, we find that typically 60% or more are at the two highest hierarchy levels (PR+MA). The *other education* group is typically spread out most widely across hierarchy levels. Given that it includes all workers without any degree, we find that this education group always shows a large share of workers at the lowest rank of hierarchy. Third, the distribution across hierarchies shifts to the top as workers accumulate experience. 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 ranks of the hierarchy than workers from the younger age group. This fact highlights again the difference between education as a typically fixed worker characteristic after labor market entry and hierarchy levels that change over the course of the life cycle. For example, for university-educated men the share of workers in management (MA) doubles from 20% to 40% when comparing the two age groups. Fourth, the results provide further evidence for a slowdown in career progression for females after age 30. While the distributions across hierarchy levels conditional on education

Table 2: Share of hierarchy levels within formal education and age groups

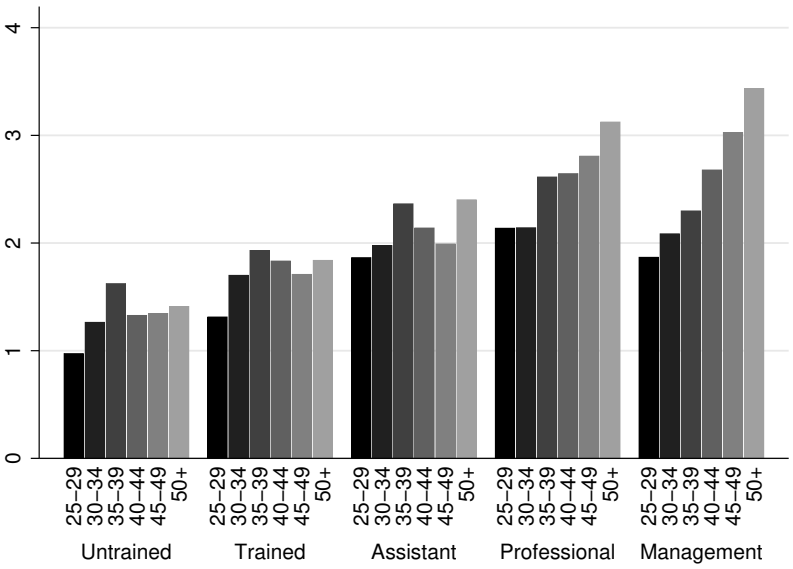
	at age 25 - 35 (in %)					at age 35 - 45 (in %)				
Education	UT	TR	AS	PR	MA	UT	TR	AS	PR	MA
Males										
Secondary	25.6	37.9	26.7	7.8	2.1	18.3	39.7	29.7	9.2	3.0
Vocational	5.5	15.7	60.7	15.7	2.5	3.5	12.7	52.4	24.6	6.8
University	1.2	2.8	27.5	48.6	19.9	0.4	1.2	13.8	44.9	39.7
other	17.9	28.9	38.3	12.1	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. Top part of the table shows male workers, bottom part female workers. Shares sum within age groups to 100. Secondary education contains all workers with secondary education but no vocational training. Vocational education refers to workers with secondary education and in addition a vocational degree. University degree refers to all workers with a university or technical college degree. Workers without reported education are in group not reported. Hierarchy groups UT/TR/AS/PR/MA refer to untrained, trained, assistants, professionals, and managers, respectively.

are very close in the younger age group, we find a substantial divergence in the hierarchy distribution between males and females in the older age group. The share of male workers with vocational training who are in jobs as professionals or managers (PR + MA) is 8 percentage points higher than for females in the age group 35 to 45. For the younger age group, the difference is roughly 1 percentage point. The descriptive analysis suggests that education and experience help with progression on the career ladder and that females progress more slowly than men. We revisit these findings in our regression analysis below. Labor market mobility to climb the job ladder is another form of human capital investment. For career progression, labor market mobility might also be important: workers go to employers who offer them career opportunities. Table 2 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. Accumulating tenure on the one hand and engaging in labor market mobility on the other hand constitutes a trade-off from the worker's perspective because mobility leads to a loss of tenure and tenure accumulation rules out mobility across employers. We therefore investigate the relationship between

tenure, labor market mobility, and career progression based on the descriptive analysis in Figure 9.

Figure 9: Tenure increase by age and hierarchy



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

Figure 9 shows how much tenure increases (in years) from one five-year age group to the next five-year-older age group, at different levels of hierarchy. If all workers stayed with their employer, the increase between age groups would be five. If everyone changed employers, the increase would be zero. We find that tenure tends to increase more strongly at higher levels of hierarchy and the increase accelerates over workers' careers. The steeper increase across hierarchies and age suggests that mobility across employers is detrimental to career progression. However, it is important to note two things. First, the increasing tenure up on the career ladder can be a result of selection when only the workers who get promoted stay with the employer. Second, even if there is a positive causal effect of tenure on promotions, then labor market mobility is still important as workers have to find the employer that offers them the opportunity to climb the career ladder. In section 5.2, we will discuss differences in organizational structures across employers and the relation to the plant component of pay. In this section, we go on and adapt the regression framework from above to jointly explore the different determinants of career progression over the life cycle.

We estimate the effect of the different determinants from the descriptive analysis on career progression relying on the synthetic panel approach from above. Since hierarchies have a

meaning in terms of log-wages, we use their estimated coefficients to measure the distance between hierarchy groups, such that we end up with a cardinal measure of hierarchy: the wage that is typically associated with it. We refer to this measure as the *hierarchy wage*. We aggregate hierarchy wages back to the cohort level and use this generated variable to estimate the effect of an employee's characteristics on his/her moving up the hierarchy ladder.[14] We estimate the average hierarchy wage hw_{ct} of a cohort c at time t as a function of that cohort's educational attainment, work experience, and tenure with its current employer. We use the average fraction of a cohort over the three sample years that has a college education or vocational training, only secondary schooling, or other education as a measure of educational attainment and interact this with experience. We estimate the following model:

$$\begin{aligned} hw_{ct} &= \gamma_c + tenure_{c,t} + tenure^2_{c,t} \\ &\quad + experience_{c,t} * (1 + education_c + gender_c) + \varepsilon_{ct} \end{aligned} \tag{5}$$

Using the synthetic panel approach the baseline effect of education on hierarchies is not identified separately from the cohort effect, we can only identify if education leads to steeper or flatter career profiles. To allow for career slopes that vary with age, we estimate coefficients separately for young, middle-aged, and experienced workers. To investigate the level effect of education that our descriptive analysis suggests, we resort to estimates from a pooled cross-sectional OLS regression that also allows us to estimate the baseline effect of education. The estimated coefficients from this regression will be biased if the hierarchy wage is a function of individual fixed effects. We discuss this issue in the robustness analysis in Appendix C.2.

Table 3 reports the estimated coefficients from the two regression approaches. The left panel of the table reports the results from the pooled cross-sectional OLS regression, in particular, the level effects from education. The right panel reports the results of the synthetic panel regression that accounts for individual fixed effects on the hierarchy wage. Looking at the left part, we find that workers without training or those summarized as *other* education enter the labor market on average at lower levels of hierarchy than workers with vocational training. Workers with a college education are found further up on the hierarchy ladder. Hence, even after controlling for other forms of human capital investment, we find a positive correlation between education and career progression. Looking at the right part with results from the panel regression, we find that workers without training and workers with a college education show steeper career paths than workers

[14] Given the ordinal nature of the hierarchy data, an ordered probit estimator would have been an alternative approach. Yet, given that we have to resort to synthetic panels in order to control for unobserved heterogeneity, this is not straightforward, because the probit model is non-linear.

Table 3: The effect of experience, education, and tenure on career progression

	Pooled Cross Section OLS			Cohort Fixed Effects		
age group	25-30	31-40	41-55	25-30	31-40	41-55
experience	1.2***	0.6***	-0.0	2.9**	0.5	-1.6***
× female	-0.4***	-0.6***	-0.2***	-0.3	-0.7***	-0.1
× college education	2.2***	0.7***	0.1***	3.5	2.2	6.7***
× only secondary education	-0.2***	-0.8***	-0.0	15.5***	6.4***	5.2***
× other education	0.6***	-0.3***	-0.4***	-8.5**	-0.2	4.9***
tenure	1.5***	1.2***	0.7***	6.9***	3.0***	2.5***
tenure^2/mean(tenure)	-0.5***	-0.3***	-0.1***	-7.8***	-1.6***	-0.6***
college education	24.2***	31.5***	41.1***			
only secondary education	-13.3***	-10.7***	-21.6***			
other education	-8.6***	-4.7***	-3.4***			
Cohort fixed effects	No	No	No	Yes	Yes	Yes
Observations	356,568	732,161	1,297,231	180	300	450
Adjusted R^2	0.20	0.25	0.29	0.89	0.82	0.97

Notes: *,**,*** indicate significance at the 10, 5, and 1 percent level, respectively. The left panel displays the regression coefficients of a regression of the hierarchy wage of a worker on tenure and experience interacted with the educational attainment of the worker and on education dummies. The left panel displays the results of a regression of the cohort-year average log hierarchy wages on tenure and experience interacted with the average educational attainment of a cohort controlling for cohort fixed effects; see equation (5). Log-Wages have been multiplied by 100 to ensure better readability. The baseline group is male workers with occupational training. We control for different male/female career profiles by including an experience gender interaction term. Cohorts are defined by birth year, gender and region (North/South/East/West).

with only vocational training. One interpretation of the steeper career paths for workers with only secondary education is that they are catching up on the career ladder as they profit more from work experience, in particular when young, exactly because they lack formal vocational training. On the other side of the distribution, workers with academic training enter at higher levels of hierarchy, but then their careers further diverge from those of the workers with vocational training. We also estimate flatter career profiles for females, both in the OLS and panel specification, but controlling for individual fixed effects, the flatter career profile is only significantly lower for women in their thirties. The difference between males and females in the panel regression is insignificant early and late in the life cycle. Job tenure shows a significantly positive coefficient also in both specifications. That is, workers in higher levels of hierarchy have been with the same firm longer, even controlling for experience and education. The negative coefficient on the quadratic term shows that the tenure effect decreases with accumulation of more tenure.

The regression results highlight an important role for human capital investment in climbing the career ladder. We find a positive effect of education on the hierarchy level and a non-monotone relation between education and the speed of career progression. Experience contributes positively to career progression. Coefficients on tenure are positive but the estimated effects have to be interpreted with care given that we did not attempt to control for potential selection effects.[15]

These findings on the determinants of career progression offer particular implications for the literature on heterogeneous agents consumption-saving models. The fact that career dynamics are a key driver of wage dynamics over the life cycle in combination with the fact that we are able to identify determinants of career progression suggests there is heterogeneity in wage risk across individuals. This wage risk heterogeneity might be known to workers at labor market entry and such known differences in wage dynamics affect through the lens of these models savings choices right from the start of working life.

4.2 Role of luck

The importance of human capital as a driver of careers suggests that an important part of career progression is not luck and that differences in career progression stem from differences in broadly defined human capital investment. However, as we show next, the conclusion that there is no role for luck in career progression is equally not warranted. In fact, the OLS regressions of hierarchy wages on worker characteristics achieve an R^2-statistics in the ballpark of 30%, the usual range of what worker characteristics can explain in terms of wage inequality.

To exemplify the role of luck for careers, 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 to be largely beyond a worker's control, and we take coworker characteristics therefore as constituting a potential source of luck in the process of career progression. The fact that coworkers influence a worker's 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 the worker's wage. 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 paper due to death). Here, 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

[15] A large literature discusses the selection biases and possible solutions when it comes to the estimation on returns to tenure. See the seminal papers by Altonji and Shakotko (1987) and Topel (1991).

Table 4: Being the silverback — the effect of experience ranking on hierarchy wages

	Relative experience			
	Most experienced		Relative 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 hierarchy 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 between one and five years older and have the same educational attainment. Experience ranking controls are described in the text. Regression sample includes all male workers age 45 to 50. 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 % level, respectively.

experience ranking. In the first case, we only include a dummy for the most-experienced worker within each peer group. In the second case, we use what we refer to as the *experience 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 female careers break in their early 30s. 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 hierarchy wages on the controls for the experience ranking. Table 4 shows the estimated coefficients from the regression with the hierarchy wage as the dependent variable. The estimated coefficients quantify a *silverback effect* — the effect of being the most or more experienced member of the peer group on hierarchy wages.

On average, we find this *silverback effect* to be statistically significant. The more experi-

enced a worker is the higher is he on the steps of 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 most experienced worker implies that the hierarchy 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 hierarchy component contributes approximately 25 log points to wage growth for 45- to 50-year-old workers, such that being the silverback increases the hierarchy 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 hierarchy wage between the least experienced member and the most experienced member in an average peer group are 3.8 log points.

The last two columns report education-specific coefficients with workers who have an apprenticeship training forming the baseline group. We find coworker effects to be heterogeneous across education groups. The baseline effect is always statistically significant. The silverback effect is significantly stronger for workers with only a secondary education for both experience rankings. Looking at the specification considering only the most-experienced worker, we also find a statistically stronger effect for workers with a college education. For the experience rank, there is no significantly different effect for workers with a college education. Workers summarized in the other education group have no significantly different effect than the baseline group in both cases. 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. Such coworkers constitute a source of luck because the existence of a more experienced coworker should be considered as being typically outside the control of a worker.

The finding that coworkers are important for career progression suggests that rivalry for jobs in the labor market is important. Staffings and promotions expose coworkers to an externality as their career opportunities deteriorate if no positions are available at the higher ranks of hierarchy at their current employer. Therefore, these externalities offer a new motive for labor market mobility across employers. If career opportunities deteriorate with the current employer, other employers might still offer opportunities at the current stage of a worker's career. Hence, our results should not be read as evidence against labor market mobility being important for human capital investment.

5 Robustness and sensitivity

This section provides robustness and sensitivity analyses of our results. First, we provide evidence that the results are likely not specific to the German labor market. We do this based on available data on the hierarchy-wage relationship for the United States. Second, we shed more light on our finding of a comparably small plant component. We relegate a further detailed robustness analysis to Appendix C. In this robustness analysis, we explore heterogeneity in the importance of job-specific wages across workers covered by collective bargaining, workers working full-time, and workers working in large plants. In summary, we find that the job-specific effect 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 job-specific 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. Overall, we find that the key findings on the importance of the job component are robust across these specifications. We relegate further details and discussion to the appendix.

5.1 Hierarchies in the US labor market

It could be that the importance of hierarchies is particular to the German labor market. For this reason and to check the robustness of our findings, we explore data for the United States from the National Compensation Survey (NCS) run by the Bureau of Labor Statistics. These data provide evidence that strongly suggests that our results on the importance of hierarchies generalize. We think that the reason for this is that hierarchies arise naturally in the organization of work (Garicano and Rossi-Hansberg, 2006; Caicedo et al., 2018) and compensation schemes based on job leveling are commonly used in the labor markets of industrialized countries.[16]

The BLS provides detailed information that describes the job-leveling procedures in the data. Its job leveling is distinct from its occupational coding,[17] although some of the information used for the occupational coding and for job leveling overlaps; see Appendix B for details. We provide corresponding evidence based on the German occupational

[16] In fact, job leveling is an entire industry in which consulting firms provide employers with tools to rank jobs and implement compensation schemes for jobs at different levels. One famous example is the point system developed by the Hay Group.

[17] Occupational classification schemes like the SOC 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.

Table 5: 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

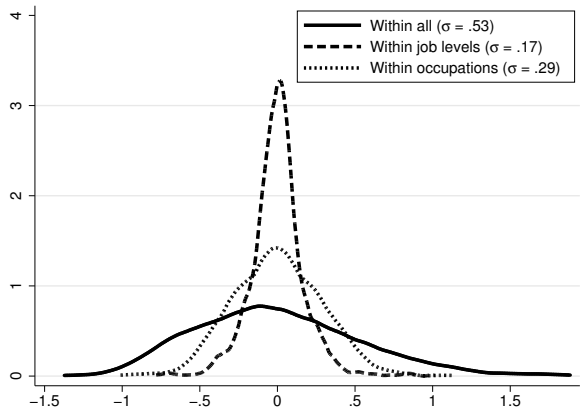
Notes: Mean wages by job level and occupational groups from the 2015 National Compensation Survey. Occupational groups follow the 2010 SOC codes. The different occupational groups correspond roughly to Management, Business & Finance, IT & Engineering, Education, Legal, Healthcare (11-29), Service (31-39), Sales and Administration (41-43), Farming, Construction, Maintenance (45-49), Production and Transportation (51-53). See SOC classification for further details. Missing fields indicate the case of too few observations for 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.

coding (KldB) discussed in Appendix A.2.

The NCS provides information on average wages by job level both across and within occupations. Table 5 shows mean wages by job level and occupational group from the 2015 NCS.[18] We see that within coarse occupational groups there is a very large variation in wages across job levels. For example, going from job level 3 paying on average 13 dollars to job level 8 paying on average 33 dollars 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 that 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 tends to have lower wages than

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

Figure 10: Wage density across occupations by job level



Notes: Kernel density estimates for within-group wage dispersion of log mean full-time wages. Solid line shows dispersion within all full-time workers. Dashed line shows within-job-level dispersion and dotted line within-occupation dispersion. Legend reports standard deviations. All data come from the 2010 National Compensation Survey. See text for further details.

the other occupation groups. 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.

For 2010, we have more disaggregated occupational information for wages by job level. In total there are 15 job levels and 307 distinct occupations. We use these data to compare the dispersion within a job level across occupations, within occupations across job levels, and the distribution across all job-level-occupation combinations. Since we do not observe the number of employees, we treat each occupation-job-level pair as one observation. Figure 10 shows the estimated kernel densities for the three distributions. We find that the wage dispersion conditional on the job level is strongly compressed relative to the unconditional wage dispersion and also relative to the wage dispersion conditional on occupations. The standard deviation of wages decreases by 45% conditioning on 307 occupations and by 68% conditioning on only 15 job levels relative to the unconditional standard deviation (see legend to Figure 10).

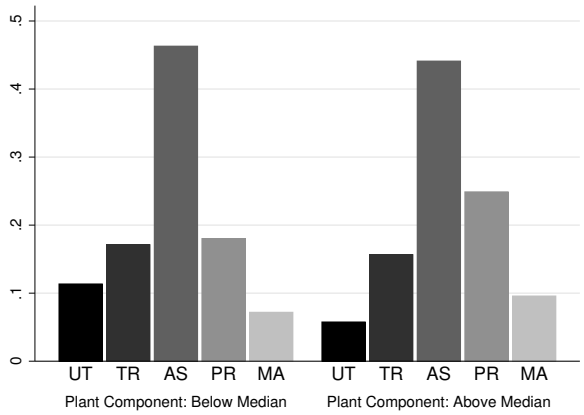
We conclude that conditional on the job level, a large part of the observed unconditional occupational wage differences disappears, which suggests that the importance of hierarchies (job levels) also applies to the US labor market.

5.2 The (un)importance of plants

One result of our analysis is that the plant component does not contribute much to increasing wage dispersion over the life cycle. At the same time, recent evidence for the US finds increasing firm differences to be a key driver of the increase in wage inequality

over the past 30 years (Song et al., 2015). At a 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 the life cycle of a worker. This implies that the plant component will pick up the organizational structure of plants, too, if we do not include information about this structure in the analysis.

Figure 11: Shares of employees by hierarchy level and plant component

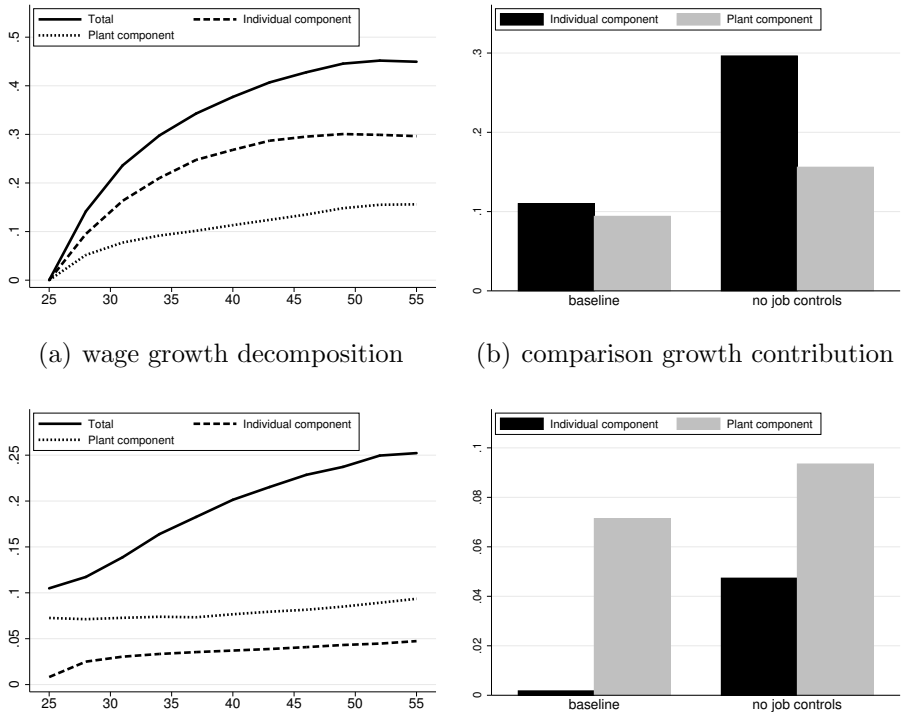


Notes: The figure shows the share of workers by hierarchy group in plants with below or above median estimated plant component $\tilde{\zeta}_b$. The median is defined on a worker basis. 67% of all plants have a below median plant component.

Figure 11 reports the share of jobs at various levels of hierarchy for jobs sorted by the corresponding plant component ζ_p. Well-paying plants offer on average more jobs at higher levels of hierarchy; only low-paying plants offer a substantial fraction of jobs on the lowest two hierarchy levels; this echoes the findings of Tåg et al. (2013) for Sweden. Note for this figure we sort plants according to whether they pay better *at all levels* of hierarchy, i.e., the plant component is not driven by having a larger share of top-level jobs. Well-paying plants are on average also substantially larger. In turn, the bottom 50% of jobs by plant component are in the bottom 67% of plants.

In turn, decomposing wages ignoring the terms that go into the job component leads to a pattern that is different from our baseline that includes this information (see Figure 13(a)). We consider males here and show results for females in Appendix C.3. The same conclusions follow. First, a substantially larger fraction of wages remains unexplained. More important, throwing away the job information leads to an overestimation by roughly 50% of the role of mobility between plants for wage growth, as Figure 13(b) shows. When we decompose the increase of wage dispersion over the life cycle, we find a qualitatively similar shift in results (see Figure 13(c)). Now, the contribution of plants to the wage inequality is inflated by 20% and both education and mobility across plants contribute significantly to the increase in wage dispersion over the life cycle; see Fig-

Figure 12: 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).

ure 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 of wage inequality by 2 log points (not displayed). This means that ignoring job information also leads to a life-cycle profile for residual wage dispersion contributing another 5 log points to the increase in wage dispersion. Observing an increase of residual wage dispersion is explained in large parts of the literature by a stochastic process with a large and persistent component. This is in stark contrast to what we find when we include the job information, where residual wage inequality is both negligible and has a flat life-cycle profile. We repeat the analysis for females in Appendix C.3 and find generally the same shifts in results.

In summary, this means that plants are important for life-cycle wage dynamics, not because of their wage level differences but because of their differences in organizational structure, whereby different plants offer different career paths. These differences in orga-

nizational structure are correlated with average plant pay and get partly picked up by the plant component when organizational structure is unobserved. Importantly, our results do not mean that labor market mobility and the question of for whom someone works do not matter for wages and wage dynamics. On the contrary, labor market mobility across plants can be a key prerequisite to career progression on the hierarchy ladder. Searching for career opportunities can be an important motivation for labor market mobility. While we find wage growth and wage dispersion not to be related to the plant itself, the organization of the plant in terms of its hierarchical structure and job composition is likely an important determinant of workers' decision about for whom to work.

6 Conclusions

The present paper analyzes wage data from the German Survey of Earnings Structure to quantify the drivers of wage growth and increasing wage dispersion over the life cycle. The data are exceptional as they allow us to relate more than 80% of wage variation to observable characteristics. We find that both wage growth and the increase in wage dispersion over the life cycle can be largely attributed to a single driver: changes in the hierarchy level of jobs as workers age. The hierarchy level of a job encodes a job's responsibilities, complexity, and independence in the organization of the work flow. Put simply, some workers climb the career ladder as they age. All other characteristics of jobs, plants, and workers explain less than 50% of wage growth and hardly any increase in wage dispersion over the life cycle.

Looking at the determinants of successful careers, we find tertiary education to be positively correlated with jobs at top hierarchy levels. In terms of speed of career progression, we find that workers without vocational training and with a college education progress on average faster on the career ladder. We provide evidence that chance likely plays a role in a worker's career, too. Specifically, we document a statistically and economically significant *silverback effect*: being a more experienced worker in a group of peers within a plant improves the chances of ending up higher on the hierarchy ladder. Across plants, we document that on average high- and low-paying plants differ in their organizational structure with high-paying plants offering more jobs at top levels of hierarchy. We think these findings have implications for at least three strands of economic research.

First, for research exploring the secular trends in the wage structure, our findings suggest that changes in organizational structures within firms are important to understand changes in the wage structure over time. If the organizational structure itself depends on technology, the skill set of the workforce, and labor market institutions, then changes such as increasing automation, rising college attainment, or reforms of the old-age pen-

sion system will induce firms to also change their organization of production. Ultimately, this will shape the life-cycle wage dynamics of worker cohorts over time.

Second, our findings seem complicated to reconcile with the prevalent assumption in search models of the labor market 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. Our results suggest that rivalry in jobs is important. Staffing and promotions 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. If career opportunities deteriorate with the current employer due to recent promotions of coworkers, other employers might still offer opportunities at the current stage of a worker's career. Approaches ignoring such externalities tend to overstate the productivity-enhancing aspects of search, the job ladder, and will understate the role of organizational structure in shaping wage inequalities, the career ladder. In any case, our results should not be read as evidence against job-search being an important element of wage dynamics. On the contrary, if the job characteristics are key for a job's remuneration, one important element of labor market search will be to find the right match in terms of a job's responsibilities with a worker's capacity to take these on. Our results further point to strong job specificity of productivity. This implies that when employer-worker matches resolve, a high-paying (highly productive) job persists for the employer and is only lost from the worker's perspective.

Third, our results appear relevant for macroeconomic models of heterogeneous agents as they shed new light on the determinants of wage risk. Our results suggest that how workers move along the organizational structure is a key determinant of wage risk. It also suggests that the average life-cycle wage growth and wage dispersion are linked because both result from career progression. By contrast, we find residual wage risk that cannot be linked to any observables to be small and with a flat life-cycle profile. If we adopt the view that the organizational structure of firms shapes wage risk, then this also scrutinizes the widely maintained assumption of the exogeneity of wage dynamics to changes in the macroeconomic environment. Macroeconomic factors, such as technological progress, demographic change, and policy reforms, under this view also change persistent wage risk and consequently impact the precautionary saving motive present in these models. The fact that we are able to identify determinants of career progression suggests that workers also know at labor market entry that their wage dynamics differ from those of other workers. Hence, this finding suggests heterogeneity in wage risk across individuals. Differences in wage dynamics affect through the lens of heterogeneous agent consumption-saving models savings choices of workers right from the start.

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A Further details on German Structure of Earnings Survey (SES)

A.1 Data collection and explanatory power of observables

The wage data in the German SES are transmitted to the statistical offices directly – and in most cases automatically – from the human resources and payroll accounting departments of plants. Therefore, the data contain very little measurement error. For that reason, and mostly because we observe the hierarchy level of a worker, explanatory variables have high explanatory power; see Table 6. The table shows the R^2 statistics from a simple linear regression of log worker wages on various sets of observables. Both hierarchies and plants are important in explaining wage dispersion. What stands out, however, is that five levels of hierarchy can explain close to 46% of wage variation. At the same time, we see that the R^2 of a regression that combines both plant and hierarchy effects is smaller than the sum of the R^2 statistics of the separate regressions. This reflects the important correlation between plants and hierarchies that we document in our analysis.

Table 6: Importance of characteristics in explaining hourly wages

	Plants	Hierarchies	Hierarchies and plants	Hierarchies, plants, occupations, education, experience, tenure, and sex	Hierarchies, 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. First column regression only on plant fixed effects, second column only on hierarchy dummies, third column on hierarchy dummies and plant fixed effects, the fourth column on hierarchy dummies, plant fixed effects, occupation dummies, education, experience, tenure, sex, and interaction dummies, and the fifth column on hierarchy dummies, plant size dummies, regional dummies, and industry dummies.

A.2 Additional details on the hierarchy variable

In the German data, the hierarchy variable is coded in five levels. Hierarchical concepts are, of course, also prevalent in collective bargaining agreements, and hence, there is a mapping from job descriptions in collective bargaining agreements to the hierarchy variable in our data. Typically, collective bargaining agreements have more detailed job descriptions and job leveling.

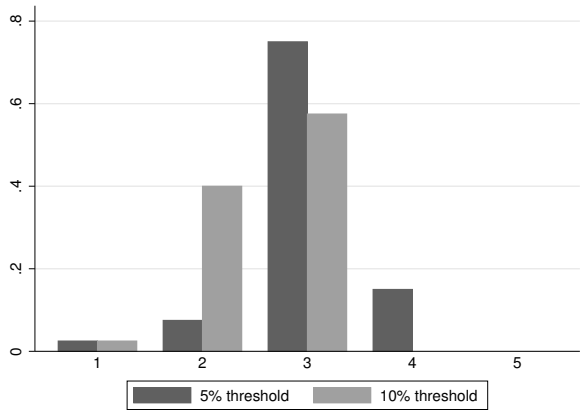
Relatedly, hierarchy levels are associated with a typical education level. Education is, however, neither a prerequisite for any hierarchy nor do all workers with a certain education work at a given hierarchy level or above. The hierarchy classification captures a functional concept within an establishment, not a qualification concept. Hence, hierarchy, while correlated with formal education, is a job- (i.e., task-)specific concept, while education captures past investments in human capital. As we have seen from Table 2, a substantial fraction of workers is employed at all hierarchy levels for virtually any level of formal education (with the exception maybe of extreme combinations) and that workers progress along the hierarchy dimension as they get older, both of which clearly indicate that formal education and the hierarchy variable measure two distinct concepts. See the discussion in section 4 for further details.

It is also important to note that hierarchy classification is distinct from the occupational classification of jobs. Hierarchy levels vertically distinguish jobs in terms of their responsibility, complexity, and independence in the organization of the work flow. Occupational classifications distinguish workers horizontally by the type of task that is done. One example is the 3-digit occupation "food preparation": within this occupation there can be different hierarchy levels capturing the differences between dishwashers, kitchen assistants, commis, chefs de partie, and sous and head chefs.

To document this fact, we explore what we call the hierarchical depth of occupations. For this, we consider 2-digit occupations and measure hierarchical depth by the share of workers within each occupation on different hierarchy levels. We use 5% and 10% as two thresholds for hierarchical depth. An occupation has a hierarchical depth of 3 if on three hierarchy levels there are at least 5% (10%) of workers from this occupation. We report the shares of occupation by hierarchical depth in Figure 13. The figure shows that the typical occupation has a hierarchical depth of three.

In addition, measures of occupation seem to be plagued with measurement error in many survey data sets, e.g., the CPS (see, e.g., Kambourov and Manovskii, 2013), which we can expect to get stronger the higher the level of disaggregation. Having said this, the recent revisions of 5-digit occupation codes have started to measure and encode job complexity (Helper/Trained/Specialist/Expert) (ISCO-08 or KldB-2010 for Germany). Table 7 shows a cross-tabulation of the last digits of the occupational classification system KldB2010 of the German employment agency against a job's hierarchy information in the 2014 SES data. While the two are positively correlated, there is still a substantial mass off diagonal.

Figure 13: Share of occupations with different hierarchical depth levels



Notes: Share of occupations with different levels of hierarchical depth. Hierarchical depth is defined as number of hierarchy levels with at least 5% (10%) of workers from an occupation. Occupation are 2-digit occupations.

B Additional details on the hierarchy variable in the US National Compensation Survey

The National Compensation Survey for the United States classifies all jobs according to their occupation and their 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 with 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.

C Sensitivity analysis and further results

We provide several sensitivity analyses to our baseline analysis from the main part of the paper. In the sensitivity analyses, we explore the effects of not being covered by a collective bargaining agreement, considering only full-time work, or focusing on large

Table 7: Cross-tabulation of hierarchy measured directly and hierarchy inferred from occupation codes

Complexity measured by occupation	Fraction of occupation (in %)	Fraction of hierarchy 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 hierarchy and job information provided by the German Statistical Office based on data from the 2014 Survey of Earnings Structure. Occupational information extracted from 5-digit occupational code (KldB 2010). First part of the table (*last digit*) shows the distribution of workers by occupational complexity across hierarchy groups. Shares sum to 100 within each row. First column (*total*) shows population share of occupation group. Second part of the table (*management occupations*) shows distribution of occupations coded as supervisors or managers across hierarchy groups. Shares sum to 100 within each row. Numbers in column total refer to share of workers coded as supervisors or managers in the total population.

establishments. We also show results if we do not control for individual fixed effects using the synthetic panel regression.

C.1 Heterogeneous returns to job and individual characteristics

For the first set of sensitivity analyses, 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 working in a large establishment. In Table 8, 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 hierarchy composition in the alternative groups compared to the baseline sample, but they are not striking.

In the first step, we test if the estimated coefficients on the additional interaction terms are statistically significant. Table 9 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

Table 8: Summary Statistics

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

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 on the different hierarchy levels in the samples, *N* is the number of observations in million of the different samples.

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 hierarchy is the key variable of the job component to explain both wage growth and dispersion over the life cycle. When we look at the coefficients of the interaction terms with the hierarchy dummies, we find them to be always strongly statistically significant (fourth row).

This means that potentially there is a deeper layer of heterogeneity than our baseline treatment explores. Yet, the test results in Table 9 only talk about statistical, not economic significance. The same careers, e.g., across hierarchy levels and occupations, can potentially mean something different when the coefficients, i.e., the returns to occupation and hierarchy, 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. Figure 14 shows the job component from the baseline specification together with the specifications from the different sensitivity specifications. For all specifications that include dummy interaction terms (no collective bargaining, full-

Table 9: Test statistics for coefficient tests

	no collective bargaining		only fulltime		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
hierarchy	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 *hierarchy* shows test statistics for the joint significance of the hierarchy-interaction dummies. See text for further details.

time, large plants) 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, i.e., we ask: what would the wage profile of workers look like if all got non-collectively bargained wages? Of course, this assumes that neither the career paths along hierarchy ladders nor the wage schedule would change when there is no collective bargaining. This has to be taken into account when comparing the different job components.[19]

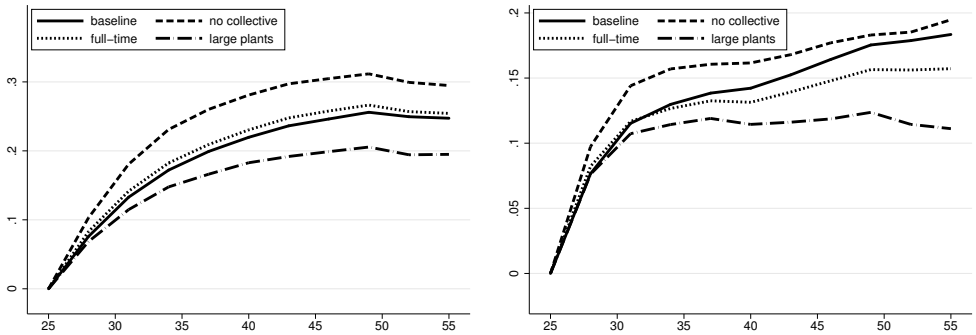
Figure 15 shows the contribution of the job component to the increase of the variance of log wages over the life cycle for the baseline and the different sensitivity specifications using the same technique. In contrast to the presentation in the main part of the paper, we removed level differences at age 25 for easier comparison.

We find that hierarchy returns in wages are more diverse when the worker is not covered by a collective bargaining agreement. This reflects the fact that there is wage compression in collectively bargained wages. In turn, the age-wage profile (for the job component) would look steeper had no worker collectively bargained wages. Analogously, without collectively bargained wages, wage dispersion would increase much more over the life cycle. For large plants, we find the reverse; yet, this is likely the effect of these plants having 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

[19]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 14: Contribution of job component to log wage change over the life cycle



(a) Males (b) Females

Notes: Contribution of the job component to log wage differences by age relative to age 25 for male (left panel) and female (right panel) workers. 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. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

wage premia for full-time workers are larger in the middle of the hierarchy distribution AS to PR but the hourly wages of the lowest and highest hierarchy workers are very similar across full time and part time.

C.2 Pooled regression without individual fixed effects

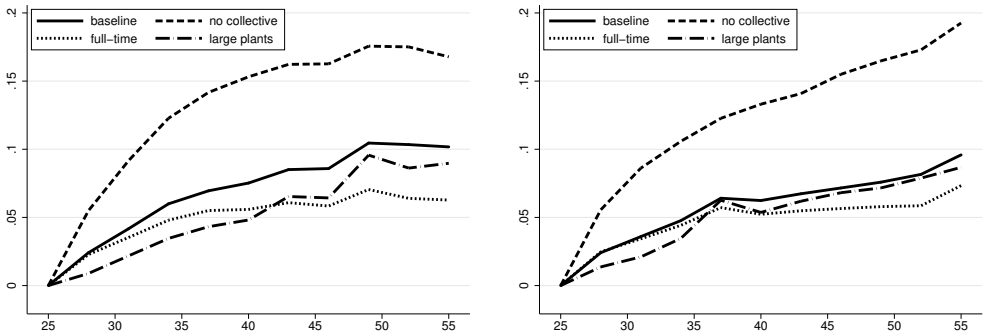
The main part of the paper uses synthetic cohorts to control for individual fixed effects that are arguably correlated with the education, career progression, and employers of workers. In this section, we run as an alternative specification a pooled OLS regression controlling for cohort effects but not 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

$$\hat{w}_{it} = \gamma_c + \beta_J \hat{J}_{it} + \beta_I \hat{I}_{it} + \hat{\epsilon}_{it} \tag{6}$$

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 16 shows the decomposition of wage growth in the individual, plant, and job component if we do not control for individual fixed effects.

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

Figure 15: Contribution of job component to variance change over the life cycle



(a) Males (b) Females

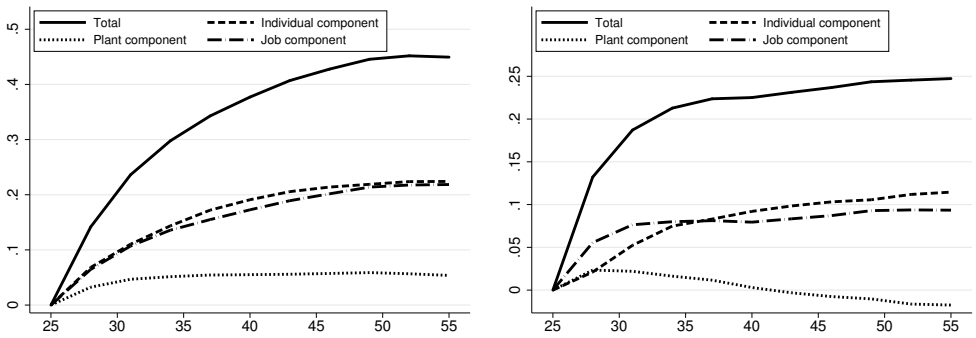
Notes: Contribution of the job component changes in the variance of log wages by age for male (left panel) and female (right panel) workers. Variances of all components are calculated by age-cohort cell and variance at age 25 is subtracted. The solid line shows the job component for the baseline from 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. All graphs show the coefficients of age dummies of a regression of the variance-covariance components on a full set of age and cohort dummies (ages defined as 3-year groups).

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 component that 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 covariances to 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.

C.3 Decomposition of wage growth and wage dispersion without job information for females

Figure 17 shows the decomposition results for wage growth and wage inequality when ignoring job information. In Figure 12, we show the decomposition for men and discuss the changes in the decomposition from ignoring information on jobs. We find the same changes in the decomposition as for males discussed in section 5.2.

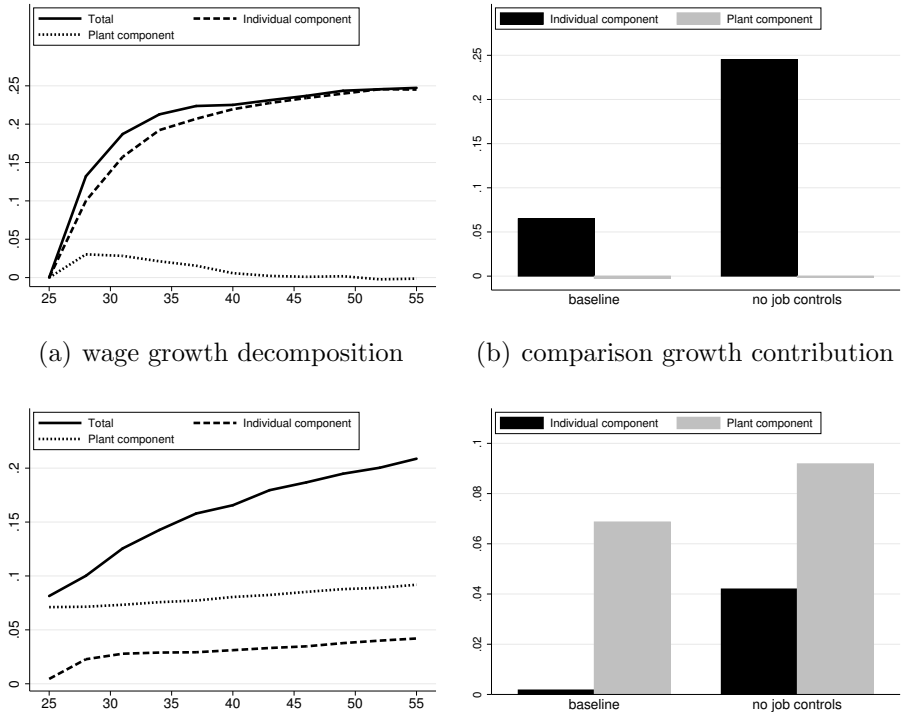
Figure 16: Wage decomposition for males and females without controlling for individual fixed effects



(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. Horizontal axis shows age and vertical axis shows log wage difference. The 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 3-year groups).

Figure 17: 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 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).