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Bad Times, Bad Jobs? How Recessions Affect Early Career Trajectories

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Abstract:
Workers who enter the labor market during recessions experience lasting earnings losses, but the role of non-pay amenities in either exacerbating or counteracting these losses remains unknown. Using population-scale data from Germany, we find that labor market entry during recessions generates a 6 percent reduction in earnings cumulated over the first 15 years of experience. Implementing a revealed-preference estimator of employer quality that aggregates information from the universe of worker moves across employers, we find that one-quarter of recession-induced earnings losses are compensated for by non-pay amenities. Purely pecuniary estimates can therefore overstate the welfare costs of labor market entry during recessions.

JEL Classifications: E32, J24, J31, J32
Keywords: Earnings inequality, recessions, non-pay amenities

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1 Introduction

Completing school and entering the labor market is a critical moment in the lives of young workers. It marks the start of a period of exploration when workers begin their first jobs, seek financial independence, and embark on new careers. It is also the moment that first exposes young workers to the large and unpredictable risk of business cycle fluctuations. Being lucky enough to start one's career in good times makes the transition to well-paying jobs and desirable careers easier, whereas the misfortune of entering during bad times makes well-paying jobs hard to find and stunts career development.[1]

Previous studies find that exposure to adverse aggregate conditions at the time of labor market entry generates an earnings penalty that is both substantial and persistent (see, for example, Kahn, 2010 and Altonji et al., 2016 for evidence from the United States and Oreopoulos et al., 2012 for evidence from Canada). These earnings penalties stem from the fact that availability of high-wage jobs is strongly procyclical (see, for example, Okun, 1973 and McLaughlin and Bils, 2001); however, the translation of short-term fluctuations in wages into long-term scarring effects is a product of several different factors. First, search frictions can hinder the movement of workers between employers, thereby extending the duration of recession-induced losses. Second, when these frictions increase with tenure, they can generate long-term human capital mismatch and reduced skill development if recession entrants do not find work in jobs, occupations, and industries in which they have already specialized (see, for example, Oreopoulos et al., 2012 and Arellano-Bover, 2022). Third, employers may be slow to learn about the true quality of recession entrants relative to expansion entrants because of greater initial mismatch. Finally, the fact that much of the labor market is characterized by long-term wage setting rather than a spot market slows down the convergence between recession entrants and expansion entrants (see, for example, Beaudry and DiNardo, 1991). Guvenen et al. (2017) provide evidence of the far-reaching consequences of these shocks by showing that much of the cross-cohort lifetime earnings inequality for men in the United States can be explained by earnings losses experienced early on in workers' careers. Their findings imply that income inequality is partially rooted in early career events.

Despite the well-developed findings on the earnings consequences of labor market entry during bad times, almost nothing is known about how recessions affect job quality beyond purely pecuniary dimensions. Do recession-affected entrants work in jobs that are worse both in terms of pay and in terms of non-pay features? Or alternatively, if non-pay amenities are priced in the labor market as compensating differentials as in Rosen (1986), do they offset some of the pecuniary losses that recessionary entrants experience? Answering these questions is critical from a welfare perspective since pay is an incomplete proxy for utility. This is especially true in light of a new and growing body of research that documents the importance of non-pay amenities that workers value in lieu of

[1]News headlines from different stages of the business cycle highlight this risk. For example, during the Great Recession: Catherine Rampell, "Many With New College Degree Find the Job Market Humbling," *New York Times*, May 8, 2011. During the strong labor market of 2016: Ben Casselman: "This Year's College Grads Are the Luckiest in a Decade," *FiveThirtyEight*, May 6, 2016. In the wake of the pandemic recession: Miguel Badia, "College Graduates Are Struggling to Make Up for the 'Lost Year' Created by the Coronavirus Pandemic," *CNBC*, July 26, 2021.

pay. For example, Mas and Pallais (2017) use a field experiment to study the value of scheduling flexibility, Wiswall and Zafar (2018) and Maestas et al. (2018) use survey data and stated preference experiments to study workers' willingness to pay for a wide range of non-pay amenities, and Sorkin (2018) and Taber and Vejlin (2020) exploit worker flows in large-scale administrative data to infer the value of non-pay amenities.

We study the pecuniary and non-pecuniary impact of graduating into a recession in three steps. First, we estimate the utility posting job search model developed in Sorkin (2018) exploiting 71 million worker moves in population-level German matched employer-employee administrative data. Implementing this approach allows us to recover estimates of employer-specific compensating differentials at scale. These estimates reveal that compensating differentials account for a share of employer-specific pay variation in Germany comparable to the share that Sorkin (2018) finds for the United States. The parallels between German and U.S. data extend even to the pattern of inter-sector earnings differences attributable to compensating differentials, suggesting that the model captures important aspects of the nature of working conditions in advanced economies. Next, we exploit the regulated timing of the German vocational training system to identify the causal effect of the unemployment rate at labor market entry on the earnings trajectories of millions of new graduates. Finally, we use detailed measures of compensation to examine the role of different features of pay in the earnings of workers who enter in good versus bad times. We find that the typical recession causes entrants to experience a 6 percent loss in earnings cumulated over the first 15 years of their careers. The core result of our paper is that one-quarter of this loss is compensated for by employer-specific non-pay amenities, which indicates that purely pecuniary comparisons overstate the welfare cost of labor market entry during recessions.

Our paper makes four contributions to the literature. First, we study the effect of cyclical shocks on early career earnings trajectories in Germany, which is a country with strong active labor market programs (ALMPs) for employment and re-training. Despite the broad availability and potentially useful role of these policy tools in mitigating the impact of cyclical shocks, our estimates of earnings penalties in Germany are comparable to those found by Oreopoulos et al. (2012) in the context of Canada, where ALMPs are less widespread.[2] Our estimates therefore suggest that worker-focused policy interventions do not easily neutralize the recession-induced earnings losses that labor market entrants experience.

While previous studies find that employer and occupational characteristics play a role in explaining recession-induced penalties (see, for example, Oyer, 2006, Oyer, 2008, Oreopoulos et al., 2012, and Rinz, 2019), the precise magnitude of employer effects' role in generating scars for recessionary entrants remains unknown. Our second contribution is to provide the first quantitative estimate of the relative importance of employer-specific factors in driving the recession-induced earnings penalty. To separate employer-specific factors from non-employer factors such as secular increases

[2] Oreopoulos et al. (2012) find that a typical recession results in a 5 percent loss of earnings cumulated over 10 years for Canadian college graduates. Estimates for recession-induced losses for labor market entrants in the United States are somewhat larger. For each percentage point increase in the unemployment rate, Kahn (2010) finds a 6 to 7 percent loss in wages that decays to 2.5 percent after 15 years.

in search frictions, changes in the value of outside options, secular slowdowns in employer learning, and long-term wage-setting policies, we rely on the two-way fixed effect decomposition of earnings developed in Abowd et al. (1999) (AKM).[3] Examining the impact of cyclical shocks on the AKM employer premia that workers obtain, we find that employers are responsible for about 32 percent of the overall earnings penalty while non-employer factors account for the remaining 68 percent.

Recession-induced losses in employer-specific pay can arise because workers match with employers that deliver smaller economic rents to their employees, because they match with employers that provide a larger share of compensation in the form of non-pay amenities, or both. AKM employer effects conflate these two forms of compensation. Our third and most important contribution is to separately unravel the role of rents and non-pay amenities in the recession-induced losses that accrue to labor market entrants. To do this, we estimate the utility associated with working for each employer using the revealed preference-based framework in Sorkin (2018). Within this framework, non-pay amenities at the employer level are measured as residual variation in AKM employer effects that remains after conditioning on employer-level utility.[4] In contrast, rents accruing to workers are measured as variation in AKM employer effects that is explained by utility. Using these rich measures of employer-specific compensation, we find that about 8 percent of the overall earnings loss faced by recessionary entrants is explained by reductions in rents while 24 percent is compensated for by non-pay amenities. This finding implies a nontrivial downward adjustment to the welfare cost of labor market entry during recessions, at least in the German context.[5]

Our results are consistent with previous studies that posit industry-specific risks and location-specific differences in the quality of life as important determinants of compensating differentials (see, for example, Rosen, 1986, 1979; Roback, 1982). Specifically, we find that industries, occupations, and locations explain the majority of the observed amenity gap between workers who enter during good versus bad times. Despite this finding, an important caveat is that our estimates on workplace-related utility may not capture other welfare-relevant consequences of young workers' exposure to adverse aggregate conditions such as differences in health or future mortality (see, for example, Maclean, 2013 and Schwandt and von Wachter, 2017).

Finally, we find that the positive amenity gap between recession entrants and expansion entrants arises from cyclical shifts in the source of hiring activity. In particular, our fourth contribution is to establish a new empirical fact showing that job creation at low-pay, high-amenity employers is less pro-cyclical than it is at high-pay, low-amenity employers. This difference is driven primarily by increases in hiring as opposed to reductions in separations. Labor market entrants who are beholden to the job offer distribution they face at entry therefore flow toward high-amenity employers

[3] Oreopoulos et al. (2012) use average employer-level pay as an outcome when examining the effects of cyclical shocks on labor market entrants. Although they find that this variable is an important determinant of earnings penalties in Canada, average employer-level pay is confounded by worker quality. The same concern is not applicable to AKM employer fixed effects.

[4] Under the revealed preference approach, employer-level utility combines all amenities associated with a workplace, including hours flexibility, job security, workplace injury and health risks, arduous working conditions, etc.

[5] In a finding related to our own, Guvenen et al. (2017) show that employer-provided benefits such as pensions and health insurance offset some of the increases in cross-cohort lifetime income inequality for men in the United States.

in recessions and toward low-amenity employers in expansions. Our finding that high- and low-amenity employers exhibit differential cyclical sensitivity in employment growth is related to research by Haltiwanger et al. (2018), who show that employment growth at high-pay employers is more cyclically sensitive than at low-pay employers. Relative to Haltiwanger et al. (2018), the novelty of our result is that it shows cyclical differences in employment growth have an amenity component, not just a pay component.

The rest of the paper is organized as follows. Section 2 describes data provided by the Institute for Employment Research (IAB) of the German Federal Employment Agency. Section 3 explains how we use the universe of matched employer-employee data to construct employer-specific measures of pay and non-pay compensation. Section 4 describes our identification strategy and sample construction. Section 5 presents our results on the impact of cyclical shocks on earnings and their sub-components. Section 6 explores mechanisms driving the changes in earnings and amenities. Section 7 examines heterogeneity across sub-groups of labor market entrants. Section 8 concludes.

2 Data

We use three different administrative data sets in our analyses. In this section we provide details on the structure of each data set and describe how it features in subsequent empirical work.

2.1 Population-Level Employment Histories

Most of our empirical analyses rely on the 2002–2018 Employee History Files (Beschäftigtenhistorik, BeH), which are linked employer-employee histories provided by the Institute for Employment Research (Institute für Arbeitsmarkt- und Berufsforschung, IAB) that cover the universe of employment subject to social security payroll tax contributions.[6] Records in the BeH are organized in terms of spells, where each spell enumerates a match between a given worker and a given employer. Spell-level information about the worker includes the start and end dates of employment, earnings, full-time or part-time status, occupation, education, date of birth, gender, nationality, and place of residence.

Establishments in the BeH, which are assigned unique time-invariant identifiers, are either single-unit plants or groups of plants owned by the same firm that operate within the same municipality and industry. We refer to establishments in our data as employers. Employer-level information includes the place of business and industry classification. Spells associated with apprenticeships in Germany's vocational training system are separately tracked in the data, which allows us to infer information on training-specific occupations and the start and end dates of training. This information is critical for our research design because it allows us to track young workers through their vocational training activity and into regular employment with day-level granularity on labor

[6]In Germany, social security payroll tax contributions cover unemployment insurance, health insurance, and old-age pensions. Civil service jobs, military service, and self-employment are not tracked in the BeH. Marginal part-time employment—or so-called mini-jobs—is tracked starting in April 1999.

market entry. In addition, the population-level scale of the BeH allows us to implement the data-hungry approaches to estimating employer-specific earnings premia as in Abowd et al. (1999) and employer-specific amenities as in Sorkin (2018). We provide additional information about the BeH in Appendix A.

2.2 Random Sample of Employment and Unemployment Benefit Histories

To calculate unemployment rates, we use the Sample of Integrated Labor Market Biographies (Stichprobe der integrierten Arbeitsmarktbiographien, SIAB) (for details, see Frodermann et al., 2021). These data comprise a longitudinal 2 percent random sample of all individuals in Germany who ever worked, claimed unemployment insurance benefits, or sought job-seeking assistance during the 1975–2019 period. In total, the sample describes the labor market histories of just over 1.9 million workers. Unlike the BeH, which is limited to only employment spells, the SIAB allows us to observe both employment and benefit receipt and contact with active labor market programs during nonemployment.[7]

Computing unemployment rates using the SIAB's detailed microdata has two distinct advantages relative to relying on published statistics. First, the microdata allow us to estimate state-level unemployment rates specifically for workers with vocational training experience. Notably, these skill-specific unemployment rates are published at the national level but not released at the state level. Second, as we will discuss in Section 4.3, the microdata allow us to more credibly estimate exposure to cyclical conditions by omitting the entering cohort of trainees from the computation of the unemployment rate.

We construct our annual unemployment rates in three steps. After excluding the set of workers who complete their apprenticeships in a given year, we assign the remaining workers with vocational training experience a status of employed, unemployed, or out of the labor force on the 15th of each month.[8] We then aggregate these observations into monthly unemployment rates by workers' state of residence. Finally, we aggregate monthly unemployment rates into yearly unemployment rates by averaging across months and weighting monthly rates by the underlying number of observations associated with each month. The resulting state-year unemployment rate is our primary independent variable of interest throughout this paper.

2.3 Administrative Wage and Labor Market Flow Panel

To study the cyclical nature of employment growth, hiring, and separations at the employer-level, we use the IAB's Administrative Wage and Labor Market Flow Panel (AWFP) (for details, see Stüber and Seth, 2017). Our analyses rely on the AWFPs measures of quarterly inflows and outflows of full-time workers for each employer as well as the end-of-quarter stock of full-time workers at each

[7] Nonemployed individuals who neither receive benefits nor seek job-finding assistance are beyond the scope of the administrative data from which the SIAB is constructed.

[8] The SIAB provides detailed information about labor market status that we aggregate to three simple categories.

employer. Although it is a standalone employer-level data set, the AWFP is constructed using matched employer-employee histories from the BeH.

3 Estimating Employer-Specific Earnings Premia and Amenities

In this section we describe how we estimate employer-specific earnings premia and employer-specific values. We explain the identification and estimation strategies involved in obtaining each of these employer-specific estimates. We then explain how we use earnings premia and values jointly to obtain employer-specific estimates of rents and non-pay amenities.

3.1 AKM Earnings Decomposition

The AKM model decomposes log earnings for worker i in year t as

$$\log(y_{it}) = \alpha_i + \psi_{j(i,t)} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + r_{it}. \tag{1}$$

In Equation (1), y_{it} is annual earnings. Person fixed effects, α_i, incorporate individual-specific skills that are rewarded equally across employers. $j(i,t)$ indexes the firm that employs worker i in year t, and the employer fixed effect, $\psi_{j(i,t)}$, is a proportional premium that is paid by employer j to all its employees. $\boldsymbol{x}_{it}$ is a vector of unrestricted year dummies as well as quadratic and cubic terms in age fully interacted with educational attainment. These controls account for aggregate and life-cycle determinants of earnings. Consistency of the parameter estimates requires that the error term, r_{it}, is uncorrelated with α_i, $\psi_{j(i,t)}$, and the $\boldsymbol{x}_{it}$. Card et al. (2013) provide a detailed discussion about the validity of the identifying assumptions specifically based on the BeH data. To facilitate research use, the IAB has estimated person and employer fixed effects over five eight-year time windows using the AKM model.[9] We rely on estimates from the 2003–2010 and 2010–2017 periods in our analyses.

Estimation of the AKM decomposition requires three sample restrictions. First, when workers have multiple jobs—that is, spells with multiple employers in a given year—only the highest paying job is selected. Second, because unobserved variation in hours confounds the identification of the employer-specific earnings premium, the estimation is restricted to workers with full-time status.[10] Finally, person and employer fixed effects are identified only within a connected set of employers, that is, a set of employers that either hire from or lose workers to other employers in the set. As noted in Andrews et al. (2008), the employer effect estimates, $\hat{\psi}_j$, are subject to sampling errors, which are made worse when they are identified by a small number of worker moves. This "limited-mobility bias" is problematic when assessing the role of employers in explaining the variance of log earnings. Although our empirical application does not focus on the variance of employer effects, it is

[9] See Bellmann et al. (2020) for additional details.

[10] To remove confounding variation in earnings that arises from differences in job spell lengths, the AKM model is fit using daily wages in the BeH. The estimated employer-earnings premium therefore accrues proportionally per day of full-time work.

worth noting that the eight-year windows used to estimate employer effects in IAB data substantially mitigate the impact of limited-mobility bias (see, for example, Bonhomme et al., 2020 and Lachowska et al., 2021).

3.2 Estimating Employer-Specific Values

Much of the literature that builds on the AKM decomposition treats the employer earnings premium as a measure of economic rents shared by workers. However, a long tradition in economics posits that employer-specific aspects of pay can vary not only because of factors such as rent sharing or efficiency wages, but also because of amenities that are priced in the labor market as compensating differentials.[11]

Building on this tradition, Sorkin (2018) proposes a novel methodology to study labor market mobility on the basis of utility rather than just pay. In his model, the voluntary movement of workers across jobs provides information about the relative utility associated with those jobs that is composed of both pay and non-pay attributes. Implementing this revealed preference argument requires three assumptions. First, all workers have the same preferences over jobs, up to an idiosyncratic draw. Second, all jobs within an employer are deemed to be identical from the standpoint of non-pay characteristics. Finally, all workers—both employed and nonemployed—search randomly from the same offer distribution.

Taking these assumptions to linked employer-employee data, Sorkin (2018) develops an estimator that aggregates the voluntary movement of workers across employers into employer-level utility, which is also referred to as employer value. Intuitively, the estimator rewards employers for making more hires from other high-quality employers and penalizes them for voluntary departures. Akin to the connectedness requirement in AKM, values are calculable only within a *strongly connected* set of employers. Strong connectivity is defined as a set of employers who both gain *and* lose workers to other employers in the set.[12]

Because employer values are estimated using a revealed preference argument, a crucial step in the procedure is to infer the probability that a given worker move is voluntary. Appendix Figure B1 illustrates how these probabilities are estimated by exploiting the hockey-stick shape of the separation hazard across employer growth rates; that is, separations at growing employers are low and stable, whereas separations at shrinking employers rise sharply. The identifying assumption is that separations from growing employers are likely to represent "expected" turnover that is fueled by voluntary quitting. In contrast, excess separations at shrinking employers are likely driven by involuntary displacement. Then, the benchmark probability that *any* employer-to-employer (EE) transition is voluntary is the average EE transition probability for growing employers. Similarly, the benchmark probability that *any* employer-to-nonemployment (EN) transition is voluntary is

[11] See, for example, Rosen (1974) and Rosen (1986) for theory, and Lucas (1977), Freeman (1978), and Brown (1980) for empirical evidence.

[12] Limited-mobility concerns associated with employer fixed effects in earnings are also relevant in the estimator proposed by Sorkin (2018) to infer employer utility. We discuss the impact of this source of estimation-induced noise in the next Section 3.3.

the average EN transition for growing employers. At shrinking employers, the excess probability of an EE or EN transition, over and above the voluntary transition probability, is defined as the involuntary transition probability.[13]

We implement the methodology developed in Sorkin (2018) using population-scale BeH data with some minor modifications to accommodate differences between U.S. employer-employee linked data to which the method was originally applied and the BeH. Appendix B provides details about the data, the estimation procedure, and model fit relative to targeted parameters. Analogous to the AKM effects, we estimate values separately for the 2003–2010 and 2010–2017 time windows.[14]

3.3 Estimating Employer-Specific Amenities

Idiosyncratic shocks in the utility posting job search model of Sorkin (2018) generate frictions that preclude free movement of workers between employers. Consequently, because utility is not equalized across employers, workers earn rents. In this framework, assume that workers' utility functions can be written as

$$V_j = \omega(\psi_j + a_j), \tag{2}$$

where V_j is the forward-looking value of working at employer j, ω is utility per log euro, ψ_j is the employer-specific earnings premium, and a_j is the employer-specific non-pay amenity. One can then rearrange Equation (2) to estimate

$$\psi_j = \pi V_j + \epsilon_j \tag{3}$$

and then obtain the residual terms $\hat{\epsilon}_j = \psi_j - \hat{\pi} V_j$. Because the residuals are orthogonal to V_j by construction, they capture components of a_j that generate variation in employer-level earnings, holding utility fixed. In the context of a profit maximizing employer, Sorkin (2018) shows that the residuals in Equation (3) arise from variation in the cost of amenity provision that is independent of V_j. The motive for employers to provide these non-pecuniary amenities is therefore analogous to the theory of compensating differentials in Rosen (1986). The fitted value, $\hat{\pi} V_j$, captures variation in pay that is correlated with utility within a frictional labor market and therefore constitutes rents.

It is worth noting that limited-mobility concerns associated with employer fixed effects in earnings are also relevant in the estimator used to infer employer value. Estimation-induced measurement error in employer values can induce attenuation bias in $\hat{\pi}$, which distorts the role of rents relative to compensating differentials. Appendix C implements a split-sample instrumental variables approach to show that bias induced by measurement error reduces $\hat{\pi}$ by at most 4 percent. The reason for this result is that we rely on relatively long window length of eight years, impose a minimum size

[13] Note that unemployment and labor force non-participation are considered the same for the purposes of this estimation procedure. Nonemployment-to-employer transitions are always assumed to be voluntary.

[14] Data from 2002 and 2018 are used to determine the source and destination of worker inflows and outflows in 2003 and 2017, respectively. Consequently, employer effects estimated in the 2003–2010 and 2010–2017 windows are neither left nor right censored.

restriction of 10 full-time workers per year for each employer, and include nonemployment as its own node in the strongly connected set. These restrictions allow us to accumulate many worker moves per employer and effectively mitigate the influence of limited-mobility bias.[15] Given that we detect an extremely small degree of attenuation, we ignore this source of bias as a first-order concern when interpreting our main findings.

To illustrate the relationship in Equation (3) graphically, Figure 1 shows studentized employer values on the horizontal axis and studentized earnings premia on the vertical axis.[16] Each dot in the figure averages over a 1 percentile bin of the employer value distribution and reveals a stable linear relationship between pay and values indicating that higher-value employers offer higher pay at approximately the same rate across the value distribution. The red lines show one standard deviation bands of the employer fixed effect distribution within each value percentile. Observing variation in employer fixed effects, holding value fixed, indicates that employers differ in pay premia even though they provide the same utility. These differences in employer-specific pay arise from differences in employer-provided non-pay amenities.

Table 1 quantifies the role of compensating differentials in Germany. The top panel shows the R^2 from estimating Equation (3), which is the share of variance in employer fixed effects that is explained by value. The residual variance share, $1 - R^2$, captures components of the employer fixed effects that are orthogonal to value, that is, the share attributable to compensating differentials. Columns (1) and (2) show estimates using BeH data from 2003 to 2010 and 2010 to 2017, respectively. For comparison, column (3) shows estimates from Sorkin (2018), which are based on U.S. data from 2000 to 2008. Across all three columns, we see that the majority of the variance in employer fixed effects is attributable to compensating differentials. In Germany, the share is 80 to 84 percent, whereas in the United States the share is 70 percent. Complementary to these results, we also find a high degree of temporal stability in the employer-specific estimates. The correlation coefficients between the two time windows are 0.83 for AKM employer fixed effects, 0.74 for values, and 0.75 for compensating differentials.[17] These estimates echo the findings in Lachowska et al. (2021), who show that AKM employer fixed effects reflect essentially permanent differences in employer-level pay policies since they remain stable even when estimated over one- or two-year time windows.

The second panel of Table 1 computes the share of variation in compensating differentials (that is, the estimated residuals, $\hat{\epsilon}_j$) explained by location and industry characteristics. State fixed effects explain 16 to 19 percent of compensating differentials in Germany, while county fixed effects explain 18 and 20 percent.[18] These estimates are consistent with the theory developed in Rosen (1979) and Roback (1982) indicating that local differences in amenities and in the cost of living are priced

[15]The average number of worker moves per node in the strongly connected set ranges from 140 in the 2003–2010 estimation window to 160 in the 2010–2017 estimation window.

[16]The figure is based on estimates of employer earnings premia and values obtained from the 2010–2017 time window.

[17]The correlation coefficients are based on 161,556 employers that are observed over both time windows.

[18]Counties in Germany are defined by administrative units known as Kreise, which are approximately equivalent to U.S. counties. There are 16 states and 401 Kreise in Germany.

into the labor market. The next two rows show that sector fixed effects explain 8 to 12 percent of compensating differentials in Germany, while the three-digit industry explains 16 to 22 percent. Comparing the estimates in columns (1) and (2) to those in column (3) reveals that location is a more important determinant of compensating differentials in Germany relative to the United States, while the converse is true for industry.[19] The last row of the table shows that interacting county and industry fixed effects explains 47 to 54 percent of the variation in compensating differentials.

To further elucidate the role of sector and industry characteristics, Panel A of Figure 2 averages employer values and earnings premia within sectors and plots those averages alongside the line of best fit, which is estimated on the underlying employer-level data. In this figure, compensating differentials appear as variation in sector-level earnings premia, holding sector-level value fixed. For example, employers in the mining sector (labeled B) pay a substantial premium relative to what would be predicted based on their average value. This pattern is consistent with the idea that employment in the mining sector is risky and unpleasant and therefore commands higher pay in the form of a compensating differential. In contrast, employers in the health and social work sector (labeled Q) pay a discount relative to what would be predicted based on their average value. This pattern indicates that employment in the health and social work sector is associated with amenities that workers value in lieu of pay. These amenities could arise, for example, because jobs in the health and social work sector are less sensitive to demand shocks and therefore carry lower employment risk. To restate the idea behind Equation (3), sectors that pay more than what is predicted by value are those with positive compensating differentials (dis-amenities), and sectors that pay less than what is predicted by value are those with negative compensating differentials (amenities). Notably, the inter-sector earnings differences presented in Panel A of Figure 2 are strikingly similar to the ones shown in U.S. data by Sorkin (2018), which provides useful validation of the underlying methodology in a different labor market.

While occupation is not observed in U.S. matched employer-employee data, it is observed in the BeH, and we exploit this added source of heterogeneity to further validate the methodology of Sorkin (2018). Panel B of Figure 2 averages employer-level values and earnings premia within two-digit occupations and plots these averages alongside the line of best fit. The occupation-level averages are constructed from employer-level data by weighting employer values and earnings premia by the relevant occupation share within each employer. As with the inter-sector differences, we see a pattern that elucidates the role of compensating differentials. For instance, workers employed in high-risk jobs such as mineral, oil, or natural gas extraction and mineral preparation (labeled 8 and 9, respectively), and carpentry, roofing, and scaffolding (labeled 45) obtain higher pay than what would be predicted by value. In contrast, workers employed in religious ministry jobs (labeled 89), bakers and confectioners (labeled 39), and family members who work in their family-owned businesses (labeled 97), obtain lower pay than what would be predicted by value.

Taken together, the results in Table 1 and Figure 2 provide important qualitative validation that

[19] Sorkin (2018) measures industry heterogeneity at the four-digit level, whereas we are limited to the three-digit level in our data.

the values we estimated have sensible economic meaning, and that the amenities obtained from the decomposition exercise in Equation (3) capture non-pay characteristics of workplaces.

4 Institutional Setting and Research Design

In this section we provide institutional details about the German apprenticeship system, discuss how we define our estimation sample, and explain our identification strategy. We provide empirical evidence that validates our research design.

4.1 The German "Dual-Training" Apprenticeship System

Apprenticeships are the most common form of higher education in Germany. During the sample period we analyze (2003–2017), vocational training graduates account for 56 percent of the annual flow of labor market entrants with higher education degrees.[20] Apprenticeship training in Germany is also known as dual vocational training because it combines workplace and classroom training in a roughly 60-40 split. The typical young worker begins their vocational training after secondary schooling by starting an employer-sponsored apprenticeship in one of approximately 350 officially recognized occupations. Employers, unions, and government agencies jointly regulate the course content and program length associated with training in each of the occupations to meet quality standards. The typical course takes about three years to complete and culminates in a qualifying examination. Trainee wages are set by collective bargaining agreements that vary by both state and occupation (Kuppe et al., 2013).

The fact that training program duration is preset is crucial, because it makes it less likely that young workers can selectively enter the labor market when cyclical conditions are favorable. As described below, this fact plays an important role in our identifying assumption, which rules out manipulation of entry timing.

4.2 Sample Construction

The BeH distinguishes between employment spells associated with apprenticeship training and those that are not. Using this information, we construct our sample of labor market entrants by first isolating all workers who are ever recorded as apprentices in the 2003–2017 BeH files. From this set of apprentices, we remove workers whose cumulative training duration was shorter than six months or longer than four years, as well as outlying workers whose last training spell occurred before age 18 or after age 28. Finally, we limit our analysis sample to individuals whose pre-apprenticeship education level includes some form of secondary school degree but does not include a university degree.[21] After imposing these restrictions, we define the date of labor market entry as the last day

[20]Statistics are based on data provided by the Federal Institute for Vocational Training (Bundesinstituts für Berufsbildung) and the Federal Statistical Office (Statistisches Bundesamt). University graduates with Bachelor's, Master's, or Doctoral degrees account for the remaining 44 percent.

[21]We impose this restriction to focus our attention on the typical educational trajectory in Germany, where workers either move from secondary school to vocational training or from secondary school to university.

on which workers are classified as trainees—all spells subsequent to that day constitute post-entry labor market activity.

Our core analyses aim to quantify how employers contribute to early career recessionary scarring. Consequently, for all post-entry years, we assign each worker an annual dominant job—that is, a single employer—for each year. For workers with multiple job holding within a year, the dominant job is the one with the highest earnings in that calendar year. We then assign employer-level characteristics to each worker-year based on this dominant job. In order to avoid shifting the sample composition based on outcome variables, we restrict the sample for our core analyses to individuals in years when their dominant job is with an employer for which AKM effects and value estimates are both available.[22] This restriction reduces an overall sample of 6,303,695 labor market entrants to 4,500,045 entrants. Panel A of Table 2 shows fixed characteristics of the full set of entrants, while Panel B shows post-entry outcomes for each potential experience year.

4.3 Identification Strategy

Using this sample and exploiting institutional features of the German apprenticeship training system, we estimate the effect of initial aggregate conditions on labor market outcomes using the following specification:

$$y_{it} = \theta_{s(i)} + \theta_{c(i)} + \theta_{e(i)} + \theta_t + \sum_{e=0}^{14} \beta_e \left[U_{sc} \times \mathbb{1}\{e(i) = e\} \right] + \boldsymbol{X}_i' \boldsymbol{\Gamma} + \nu_{it}. \quad (4)$$

In Equation (4), $\theta_{s(i)}$ are state-of-training fixed effects, $\theta_{c(i)}$ are year-of-entry fixed effects, $\theta_{e(i)}$ are potential experience (year minus year of entry) fixed effects, and θ_t are calendar year fixed effects.[23]

Our independent variable of interest is the unemployment rate, U_{sc}, which captures the exposure of individuals entering the labor market in state s and year c to aggregate conditions at the time of entry. When computing U_{sc}, we exclude from the SIAB microdata all individuals who enter the labor market in year c. This leave-cohort-out approach removes any dependence between U_{sc} and ν_{it} that comes from cohort quality, thereby providing a better measure of cohort-specific exposure to aggregate shocks.[24] The coefficients of interest, β_e, trace out the impact of a 1 percentage point increase in U_{sc} on labor market outcomes for workers with potential experience e. The vector $\boldsymbol{X}_i$ includes a set of fixed effects that control for training occupation, gender, German citizenship, the level of educational attainment prior to training, age at the time of labor market entry, and the month of labor market entry.[25] Standard errors for estimates obtained using Equation (4) are

[22] As noted in Sections 3.1 and 3.2, this restriction amounts to analyzing individuals when they work at full-time jobs within a strongly connected set of employers that each have 10 or more full-time workers per year.

[23] As in Oreopoulos et al. (2012), we identify $\theta_{c(i)}$, $\theta_{e(i)}$, and θ_t by dropping an extra calendar year fixed effect.

[24] We can employ this strategy because we are able to construct unemployment rates tailored to our application using detailed data from the SIAB. To our knowledge, we are the first to address this endogeneity problem in the literature on labor market entry.

[25] Recall that career start, or labor market entry, is defined as the last day on which workers are observed as trainees in the BeH. Forty-five percent of trainees graduate in June or July (the usual exit exam period), while another 20 percent (comprising mostly those who take the exam early) graduate in January.

clustered at the state (where the training took place) level.

Our identifying assumption is that unemployment rates prevailing at the time of labor market entry are unrelated to unobserved factors that determine earnings, conditional on fixed effects and predetermined controls $\boldsymbol{X}_i$. This assumption encompasses two key points. First, workers with particular unobserved characteristics do not manipulate their initial labor market conditions by re-timing their entry, by switching training occupations, or by failing to complete their apprenticeships. We present evidence consistent with this first point in the next subsection. Second, the introduction of a cohort that is particularly bad (good) in terms of unobserved characteristics is not responsible for adverse (benign) aggregate conditions. We address this concern using the leave-cohort-out strategy described above.

4.4 Evidence Consistent with Identifying Assumption

We formally test whether workers' training-specific outcomes vary based on aggregate labor market conditions at entry by estimating the following cross-sectional adaptation of Equation (4):

$$[\text{Placebo Outcome}]_i = \theta_{s(i)} + \theta_{c(i)} + \gamma U_{sc} + \boldsymbol{X}_i'\boldsymbol{\Gamma} + \nu_{it}. \tag{5}$$

We estimate this regression using three different placebo outcomes. We first consider log training duration. Sensitivity of this variable to the unemployment rate at entry captures whether workers selectively time their entry in response to cyclical conditions. We next consider an indicator variable that measures whether workers maintain the same occupation from the start through the end of training. This variable measures in-training stability in workers' area of specialization. Sensitivity of this variable to the unemployment rate at entry captures whether workers respond to expected changes in the demand for specific skills by switching to a new occupation. Finally, we consider whether workers pass an end-of-training qualifying exam and obtain a diploma. Sensitivity of this variable to the unemployment rate at entry captures whether workers selectively drop out of their programs based on cyclical conditions. For each test, the parameter γ captures the effect of the unemployment rate at entry on the outcome of interest.

As shown in Table 3, we do not find any evidence that training-related outcomes vary based on aggregate conditions at the time of labor market entry, thereby lending credence to our identifying assumptions. Our 95 percent confidence interval excludes entry delays longer than 14 days due to a one standard deviation increase in U_{sc}. Similarly, we can rule out increases in training occupation switching of more than 2.8 percent relative to the mean. Trainees are at most 0.2 percent more likely or 0.2 percent less likely to obtain their training certificate when faced with a one standard deviation increase in U_{sc}. Both statistically and economically, we do not detect significant manipulation of entry timing, occupation specialization, or successful program completion by trainees in response to their future labor market conditions at entry.

5 The Effect of Cyclical Shocks on Early Career Outcomes

In this section we study the effect of cyclical shocks on the early career trajectories of young workers. We show that labor market entry during recessions generates a loss in earnings of 6 percent cumulated over 15 years. We find that 32 percent of the total earnings penalty is attributable to employer effects. We further find that 8 percent of the earnings penalty is due to losses in employer-specific rents, while 24 percent of the penalty is compensated for by employer-specific amenities.

5.1 Long-Term Earnings Losses

Our first key result replicates findings of previous studies in a new setting by showing the effect of aggregate shocks on early career earnings trajectories. Figure 3 shows estimates of the β_e coefficients, which measure the effect of a 1 percentage point increase in the unemployment rate at entry on log earnings in subsequent years. Labor market slack at the time of entry generates an initial drop in pay that takes longer than a decade to overcome.[26]

To assess the effect of a recession-sized shock on earnings trajectories, we rescale the change in the unemployment rate at entry to represent a one standard deviation increase in the state-level unemployment rate. We then consolidate these effects into a single estimate given by the percentage loss in the present discounted value (PDV) of real earnings. This calculation is written as:

$$100 \times \left(1 - \frac{\sum_{e=0}^{14}\left[\bar{y}_e(1+\sigma_U\hat{\beta}_e)(1+r)^{-e}\right]}{\sum_{e=0}^{14}\left[\bar{y}_e(1+r)^{-e}\right]}\right). \tag{6}$$

In Equation (6), $\bar{y}_e$ is mean real earnings in potential experience year e, σ_U is the standard deviation in the state-level unemployment rate, and r is the discount rate. In our data, $\sigma_U = 3.80$, and we assume $r = 0.05$. In the sample of workers restricted to annual dominant full-time jobs, the typical recession induces a 5.59 percent loss in the PDV of earnings. Although it is calculated in a different institutional setting, this estimate is quantitatively similar to the 5 percent earnings loss accrued over 10 years for the average Canadian recession graduate estimated in Oreopoulos et al. (2012).

5.2 Employer-Specific Versus Non-Employer Factors

To what extent are recession-induced earnings losses generated purely by employer factors, and to what extent are they generated by forces that are not specific to employers? To answer these questions, we use AKM employer fixed effects in earnings as the outcome variable in Equation (4). Before interpreting the split between employer and non-employer factors, it is important to note that our estimates capture low-frequency variation in employer-specific compensation since we rely on AKM employer effects estimated separately over two eight-year windows. The contribution of

[26] While we focus on workers who are employed in their full-time dominant jobs throughout the main text, Appendix E.2 examines total earnings, and Appendix Figure D3 shows the effect of recessionary entry on full-time employment propensity.

employer-specific factors to the overall earnings penalty can therefore be thought of as isolating temporally stable aspects of employer-wide pay policies. In the data, employer-level pay policies are, in fact, highly persistent. AKM employer effects, rents, and compensating differentials all exhibit strong temporal stability across the two estimation windows with correlation coefficients between 0.74 and 0.83. Similarly, Lachowska et al. (2021) find highly stable AKM employer effects over even narrower one- and two-year windows.[27] High-frequency variation in employer effects cannot be identified in our setting and this variation is subsumed into non-employer forces in our decomposition exercise.

Figure 4 plots coefficients from estimating Equation (4) with AKM employer effects as the outcome in blue alongside the log earnings outcomes. We see that employer effects dip at entry and then catch up steadily, indicating that workers who enter the labor market during recessions systematically match with lower-paying employers but subsequently take bigger steps to close the gap. When we apply these coefficients to the formula in Equation (6), the result indicates that employer effects explain about 32 percent of the recession-induced loss in the PDV of earnings.[28]

The relatively large effect of employer-specific factors in early career earnings penalties could arise due to losses in rents or changes in the mix of pay and non-pay amenities. While valuable in ascertaining the role of employer-specific factors, the AKM employer effects on their own do not help to resolve this distinction. To break down these hidden features of employer-specific aspects of pay, we use the rent component of the AKM employer effect as an outcome variable in Equation (4) and plot the coefficients in orange in Figure 4. Notably, we see that the rent penalties are consistently smaller than the overall loss in employer-specific pay. This difference between rents and AKM employer effects is driven by smaller compensating differentials, which indicates that recession-affected workers obtain more of their compensation in the form of employer-provided amenities. Appendix Figure D1 plots the estimated $\hat{\beta}$ from these outcomes separately, with standard errors.

The relative magnitude of the different features of pay penalties is summarized in column 1 of Table 4: Of the 5.59 percent loss in the PDV of earnings, employer-specific factors account for 1.79 percentage points, or about 32 percent. Reductions in rents account for about 0.5 percentage point or about 8 percent. Finally, gains in non-pay amenities account for 1.32 percentage points or about 24 percent.[29] A novel and welfare-relevant conclusion that emerges from these estimates is that focusing purely on pecuniary losses and ignoring the role of employer-provided amenities overstates the cost of labor market entry during recessions by about 24 percent.

In order to further understand this result, we examine the role of industry, occupation, and lo-

[27]We assign the AKM employer effects estimated within each of the two time windows (2003 to 2010 and 2010 to 2017) to the years falling within each window. We assign estimates from the second time window to 2011 data. We follow the same assignment procedure for rents and compensating differentials.

[28]Appendix D explains how we apply the PDV formula to infer the role of employer effects in the PDV of earnings losses.

[29]As shown in Appendix C, we find that the impact of limited-mobility bias on our estimates is ignorably small with rents being estimated within 96 percent of their true value. Ad-hoc factoring in this correction would imply that the role of rents in the pay penalties experienced by recession entrants would rise from 0.47 to 0.49 percentage point while the role of compensating differentials would fall from 1.32 to 1.30 percentage points (1.79-0.49). These adjustments have no meaningful impact on our conclusions.

cation characteristics in explaining the non-pay amenity gain obtained by recessionary labor market entrants. To do this, we first remove industry-by-county fixed effects from the employer-specific amenity estimates ($-\hat{\epsilon}_j$ from Equation (3)). We then use this residualized estimate of amenities as the outcome and re-estimate Equation (4). In this person-year-level regression, we also control for occupation fixed effects to absorb variation in amenities that is attributable to occupation-specific characteristics. Strikingly, we find that after we net out industry-by-county and occupation fixed effects, the non-pay amenity gains obtained by recessionary labor market entrants shrink by 82 percent. Industry effects alone shrink the amenity gap by 40 percent.

These results generate two important takeaways. First, although amenities are measured as residuals in our framework, the substantial role of industry, occupation, and location in explaining the amenity gap between recessionary and expansionary entrants highlights that commonly posited sources of compensating differentials including industry- and occupation-related risks as well as local differences in the quality of life are priced in the labor market (see, for example, Rosen, 1986, 1979; Roback, 1982). Second, the quantitative importance of industry effects in explaining the amenity gap provides evidence that earnings penalties experienced by workers who enter low-paying industries during recessions are partly attributable to a compensating differential channel (and vice versa during expansions).[30] Appendix Section E.4 provides a visual illustration of the results from this analysis.

Having evaluated the impact of employer-driven changes in compensation, we turn finally to the impact of non-employer factors, which are shown in the last row of column 1 of Table 4. We see that forces such as human capital mismatch, changes in outside offers, slow market-wide employer learning, and infrequent wage renegotiation account for 3.80 percentage points, or about 68 percent of the overall loss in the PDV of earnings. From a policy perspective it is notable that these forces are the dominant source of recession-induced earnings penalties even in an environment where workers have access to active labor market programs such as retraining and job-search assistance. These findings suggest that worker-focused policies do not easily neutralize the recession-induced earnings losses that young workers experience.

5.3 Entry Conditions and the Early Career Job Ladder

While our analysis so far has focused on relative differences between cohorts, we now turn to exploring the career paths of young workers in absolute terms. Our innovation of using employer-specific measures allows us to visualize the early career job ladder not only in terms of pay but also in terms of job quality.

Figure 5 plots the year-by-year trajectory of labor market entrants in the (studentized) employer fixed effect and employer value dimensions. For comparison, the gray dashed line plots a fitted line estimated from Equation (3), showing the average relationship between (studentized) employer fixed effects and values.[31] Recall that employers depicted above the gray dashed line provide workers

[30] For instance, McLaughlin and Bils (2001), who study cyclical upgrading, conjecture that compensating differentials could play a role in explaining cyclical wage changes.

[31] The vertical distance between the plotted early career trajectories (in blue squares and orange diamonds) and the

with positive compensating differentials. To obtain the employer quality (V) coordinates of the job ladder, we first fit Equation (4) using employer value as the outcome. We then obtain predicted values from this regression for each level of potential experience using counterfactual values of the unemployment rate at labor market entry. At entry, the "Low Initial U" group faces the 25th percentile of the unemployment rate in the state where they trained over the sample period, whereas the "High Initial U" group faces the 75th percentile of their training state's unemployment rate over the sample period at entry. To obtain the employer-specific pay (ψ) coordinates of the job ladder, we conduct the same exercise using AKM employer effects as the outcome.

The overall shape of Figure 5 presents a novel look at how career paths evolve in individuals' first 15 years of work. Regardless of entry conditions, there appears to be a uniform movement of the early career job ladder in a northwest direction. This movement is steeper than the fitted line estimated from Equation (3), indicating that workers are trading non-pay amenities for pecuniary compensation as they progress in their careers for at least their first 10 years. There is some indication that this trade-off slows down (and may even reverse itself) once workers accumulate 11 or more years of potential experience.

Comparing across counterfactual scenarios reveals a second set of insights. Workers exposed to high unemployment rates at entry have to make bigger leaps up the job ladder to catch up to the trajectories they would have if they had entered the labor market in a low-unemployment-rate environment. As implied by the decline in rents from Figure 4, this is true in terms of employer-specific pay *and* employer quality. Consequently, recessionary entrants do not work for better employers on either dimension of our augmented job ladder. Figure 5 reveals that the amenity gap arises because of the difference in the position of the early career job ladder for each type of entrant relative to the average relationship between ψ and V, which is given by the gray dashed line. Comparing the vertical distance between the orange diamonds and blue squares, one sees that the orange diamonds are closer to the gray dashed line for the first 10 years of potential experience. Indeed, this recession-induced shift in the job ladder generates an amenity buffer for workers who enter the labor market in bad times. Yet, while it is the case that recessionary entrants work for employers that offer more amenities compared with the employers that hire non-recessionary entrants, this difference is not enough to offset a large reduction in employer-specific pay. The result is a small overall decline in employer quality.

6 Mechanisms that Explain Our Findings

In this section we examine mechanisms that explain our findings. We first show that recession-induced earnings losses are coincident with displacement from employers, occupations, industries, and locations where workers trained. We then show that high-amenity employers are more likely to grow in recessions relative to low-amenity employers, a shift driven primarily by hires rather than

average relationship between V and ψ (gray dashed line) arises because the average relationship is based on moves made by *all* workers, not just those made by labor market entrants. This distance thus reflects the fact that younger workers are more likely to be employed in low-amenity jobs.

separations. This cyclical shift in the source of hiring activity pulls labor market entrants toward high-amenity employers in recessions and toward low-amenity employers in expansions, thereby generating the amenity gaps that we observe.

6.1 Mechanism 1: Displacement

Figure 6 shows that recession-affected entrants are displaced from the employers, occupations, industries, and locations where they acquired specialized training as apprentices. We measure these displacement propensities by estimating Equation (4) using indicator variables for working for one's training employer, within one's two-digit training occupation, within one's two-digit training industry, and within one's state, respectively. In panels A, B, and C, the rate of relative dislocation peaks at roughly 0.75 to 1 percentage point in workers' second year of potential experience, which is coincident with the deepest loss in earnings.[32] In panel D, relative dislocation continues throughout the window, peaking at roughly 1.2 percentage points by year 14 of potential experience. Notably, displacement propensities remain significantly elevated for more than a decade after entry, which indicates that many recession-affected workers experience a permanent shift away from the skill set in which they had invested during vocational training relative to workers who enter in expansions.

Because training employers are important contributors to earnings growth in the German context, the displacement we see in panel A of Figure 6 suggests that there are strong parallels between labor market entry during adverse cyclical conditions and the unemployment scar that follows involuntary job loss (see, for example, Jacobson et al., 1993, von Wachter and Bender, 2006, and Davis and von Wachter, 2011). Furthermore, mismatch in occupation- and industry-specific human capital engendered by the displacement shown in panels B and C further contributes to earnings penalties. This type of mismatch also has analogs in the literature that proposes mechanisms for earnings losses following job loss (see, for example, Jarosch, 2015 and Krolikowski, 2017).

6.2 Mechanism 2: Cyclical Changes in the Source of Employment Growth

Having shown the importance of displacement in driving earnings losses, we now turn to investigate why recessionary labor market entrants are more likely to match with high-amenity employers. We focus in particular on cyclical changes in the types of employers to which workers flow. To do this, we first construct estimates of annual employment growth, hiring rates, and separation rates using AWFP data. As in Davis and Haltiwanger (1992), each rate is measured as changes in full-time employment flows normalized by mean employer size from year $t-1$ through year t. For example, the growth rate of employer j in year t is given by

$$g_{j,t} = \frac{\text{emp}_{j,t} - \text{emp}_{j,t-1}}{(\text{emp}_{j,t} + \text{emp}_{j,t-1})/2}, \tag{7}$$

[32] The initial dip, both in earnings and in all three displacement propensities, arises because recession-affected workers are slightly more likely to be retained by their training employers in the year of entry relative to the years immediately following entry.

where $\text{emp}_{j,t}$ is the number of full-time workers at the end of the fourth quarter of year t. We replace the numerator in Equation (7) with the change in worker inflows when computing the hiring rate and with the change in worker outflows when computing the separation rate. We then estimate the cyclical behavior of employment growth rates, hiring rates, and separation rates at high- and low-amenity employers using employer-level data with the following specification:

$$f_{jt} = \alpha_{k(j)} + \gamma_U \Delta\check{U}_{st} + \gamma_a \times \mathbf{1}(\check{a}_j > \tilde{a}_j) + \gamma_{int}(\Delta\check{U}_{st} \times \mathbf{1}(\check{a}_j > \tilde{a}_j)) + \varepsilon_{jt}. \tag{8}$$

In Equation (8), f_{jt} measures the employer-level growth rate, hiring rate, or separation rate in year t; $\alpha_{k(j)}$ is an industry fixed effect; $\Delta\check{U}_{st}$ is the change in the state-level unemployment rate from year $t-1$ to year t; and $\mathbf{1}(\check{a}_j > \tilde{a}_j)$ is a dummy variable that captures whether employer j has above-median amenities.[33] We construct $\check{U}_{st}$ from the SIAB using all worker types in order to capture employer-level exposure to cyclical conditions.[34] γ_U measures the sensitivity of employment growth rates, hiring rates, and separation rates to fluctuations in the unemployment rate. γ_a measures level differences in the same outcomes between low- and high-amenity employers. The key coefficient of interest is γ_{int}, which measures cyclical differences in the sensitivity of employment growth, hiring rates, and separation rates at high-amenity employers relative to low-amenity employers. To interpret these coefficients in terms of aggregate changes, we weight each employer-year observation by mean employment size as measured by the denominator in Equation (7).

Table 5 shows coefficients estimated using Equation (8) over the 2003–2017 sample period. Column 1 shows that a 1 percentage point increase in the unemployment rate induces a 0.58 percentage point reduction in employment growth, which reflects the slowdown in job creation during recessions. This effect is markedly weaker among high-amenity employers, as is evident from the interaction term coefficient of 0.48. Another way to state this result is that high-amenity employers become more important sources of employment growth in recessions, whereas low-amenity employers become more important sources of employment growth in expansions. This finding is closely related to the finding by Haltiwanger et al. (2018), who show that high-paying employers exhibit more cyclically sensitive employment growth compared with low-paying employers. Our result is also related to the finding by Moscarini and Postel-Vinay (2012), who show that small employers are more important sources of employment growth in recessions, whereas large employers are more important sources of employment growth in expansions. Notably, the correlation between employer size and amenities is only 0.08, which indicates that the differential cyclical sensitivity of employment growth between high- and low-amenity employers does not stem purely from size but instead captures a novel facet of employer heterogeneity in response to cyclical shocks.

Given that the growth rate in employment equals the hiring rate minus the separation rate,

[33] Amenities, $\check{a}_j$, are measured as $-\hat{\epsilon}_j$ from Equation (3). $\tilde{a}_j$ is the median level of amenities. Recall that employers can have two different estimates of $\check{a}_j$: one for the 2003–2010 time window and one for the 2010–2017 time window. We compute medians separately for each window and assign employers to the above- or below-median groups within each time window.

[34] Note that this is different from the unemployment rate used in Equation (4), which omits the entering cohort in each year and is specific to workers with vocational training experience.

we separately investigate each of these margins in columns 2 and 3 of Table 5. Comparing coefficients in the first row of these two columns shows that cyclical reductions in employment growth rates are driven primarily by reduced hiring activity. This feature of employment dynamics likely reflects strong employment protections in Germany that encourage employers faced with adverse shocks to adjust labor demand either through attrition or by relying on short-term wage insurance (*Kurzarbeit*) as opposed to layoffs. The interaction term coefficients underscore the same pattern: Differential growth rates at high-amenity employers arise largely from increased hiring activity as opposed to reductions in separation rates.[35]

Taken together, the estimates in Table 5 suggest that job creation shifts, in relative terms, toward high-amenity employers in recessions and toward low-amenity employers in expansions and that these shifts occur primarily through the hiring margin. A consequence of this cyclical pattern is that labor market entrants, who are beholden to the offer distribution they face at entry, disproportionately flow toward high-amenity employers in recessions and toward low-amenity employers in expansions. This shift in the source of hiring activity gives rise to the observed positive amenity gap between recession and expansion entrants.

7 Heterogeneity Analysis

In this section we study how our results vary across different groups of labor market entrants. For each of the sub-group analyses, which are shown as columns in Table 4, we report the PDV loss in earnings, its breakdown into employer and non-employer factors, and the breakdown of employer effects into rents and compensating differentials.

7.1 Comparing Skill Groups

To divide labor market entrants in our sample by skill level, we first regress log full-time dominant job earnings on the calendar year and potential experience fixed effects to absorb aggregate effects as well as common, experience-related growth in earnings. We then average the residuals within occupations and classify occupations with above-median residuals as high-paying occupations and those with below-median residuals as low-paying occupations. Finally, we split entrants on the basis of training occupations: Workers who complete their training in high-paying occupations are classified as high skill, while those who complete their training in low-paying occupations are classified as low skill.

Columns 2 and 3 of of Table 4 present the decomposition of PDV earnings losses for low- and high-skilled workers, respectively. Comparing the first row in each column shows that low-skilled workers experience earnings losses that are about 0.12 percentage point greater than high-skilled workers' earnings losses. Losses in the employer-specific component are not as important for workers

[35] The coefficients are very similar in regressions estimated without industry fixed effects, which indicates that cyclical differences in job creation activity between high- and low-amenity employers is primarily a within-industry phenomenon.

trained in lower-paying occupations as they are for workers trained in higher-paying occupations. Another way to state this result is that penalties that are not employer specific such as changes in the value of outside options, human capital mismatch, and slow market-wide employer learning hurt low-potential earners more than high-potential ones. A second notable feature of the estimates is that amenities play a smaller compensatory role for low-potential-earnings workers, accounting for about 19 percent (1.07/5.56 percentage points) of the loss in earnings. For high-skilled workers, they account for 25 percent (1.36/5.45 percentage points). Taken together, these findings show that workers trained in lower-paying occupations not only experience deeper overall earnings losses but also benefit less from offsetting employer-provided amenities compared with high-skilled entrants.

7.2 Comparing Men and Women

Columns 4 and 5 of Table 4 present the decomposition of PDV earnings losses for men and women, respectively. As we see from the first row of each column, male entrants experience markedly worse penalties in the face of recessionary shock, with PDV earnings losses that are about 1.7 percentage points larger than those experienced by female entrants. Losses in employer-specific pay premia account for 43 percent (1.89/4.44 percentage points) of the full-time earnings loss for women, whereas they account for a substantially lower 28 percent (1.70/6.11 percentage points) share for men. It is notable that employer-specific amenities have a strikingly large compensatory effect for women, accounting for one-third (1.49/4.44 percentage points) of the overall loss in earnings. In contrast, they account for one-fifth (1.2/6.11 percentage points) of the loss for men. These estimates highlight that when measured purely in pecuniary terms, the welfare consequences of labor market entry during a recession are substantially overstated for women—even more so than they are for the average worker. These findings on gender differences could arise because women select jobs with lower cyclical earnings risk or because women accrue skills that are better rewarded during downturns. Investigating these underlying mechanisms remains an important subject for future research.

8 Conclusion

In this paper we provide a new perspective on the costs that cyclical shocks impose on young workers. Using administrative employer-employee linked data from Germany, we first replicate the major finding of existing research showing that adverse cyclical conditions at labor market entry generate persistent earnings losses on affected workers. Using the AKM decomposition, we find that employer-specific pay premia account for 32 percent of the overall earnings loss, which highlights that recessions substantially change the types of employers with which workers match. We then estimate a utility posting job search model by aggregating the universe of worker moves between employers. This revealed-preference-based approach to estimating employer-specific utility allows us to infer rents and non-pay amenities associated with each workplace in the data. With these rich measures of compensation in hand, we find that 8 percent of the recession-induced loss in earnings is due to losses in employer-specific rents, whereas 24 percent is compensated for by non-pay amenities. Notably, the majority of the estimated amenity gap is explained by industry, occupation, and location characteristics. Our findings therefore show that focusing on earnings losses alone overstates the welfare consequences of labor market entry during recessionary periods.

An important qualifier is that our conclusions are specific to the labor market in Germany, which differs substantially in terms of employment protections, unemployment benefit generosity, job-search assistance, retraining programs and health-care provision compared with the United States and Canada, the two other countries for which recession-induced earnings losses have been studied. Furthermore, the welfare consequences that we focus on are employer specific and do not account for other important factors such as health and well-being or consumption.

Caveats notwithstanding, the employer-specific amenities that we estimate using IAB data could be used to shed light on several broad questions. For example, our results suggest that the sullying effect of recessions is not as severe for labor market entrants when we account for employer provision of non-pay amenities, but does this apply more broadly to other groups of workers, or is it a specific feature of the early career job ladder? Moving beyond cyclical shocks, what is the relative importance of non-pay amenities over the life cycle, and do they correlate with labor supply decisions? Do the optimal designs of tax and transfer policies such as unemployment insurance change when one accounts for employer-provided amenities? How do employer- and worker-level survey reports of workplace quality relate to the amenities that workers appear to value through their revealed preference choices? Providing answers to these questions opens promising avenues for future research.

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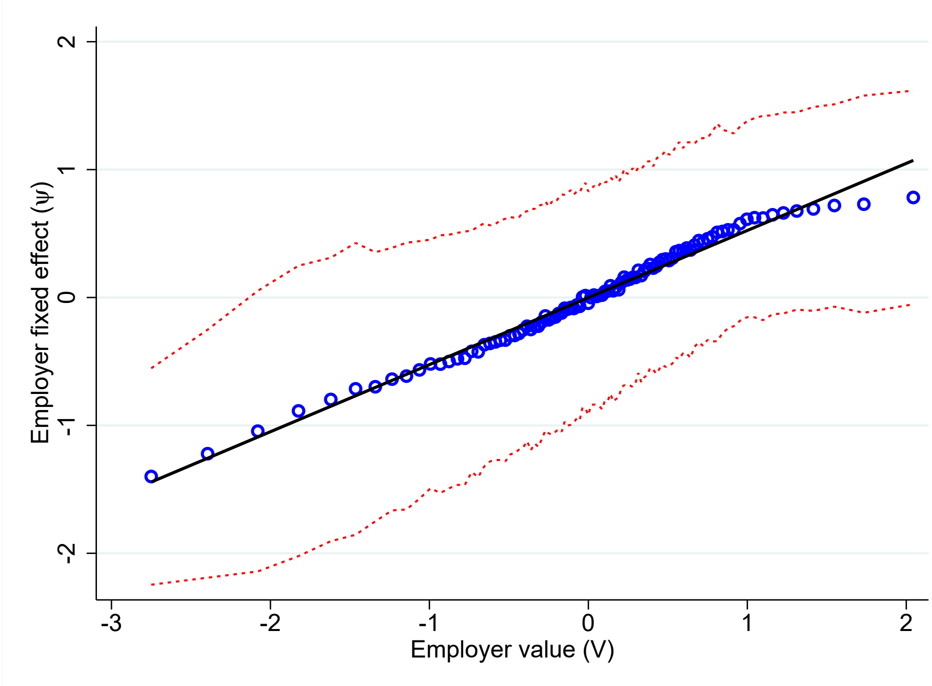
Figures and Tables

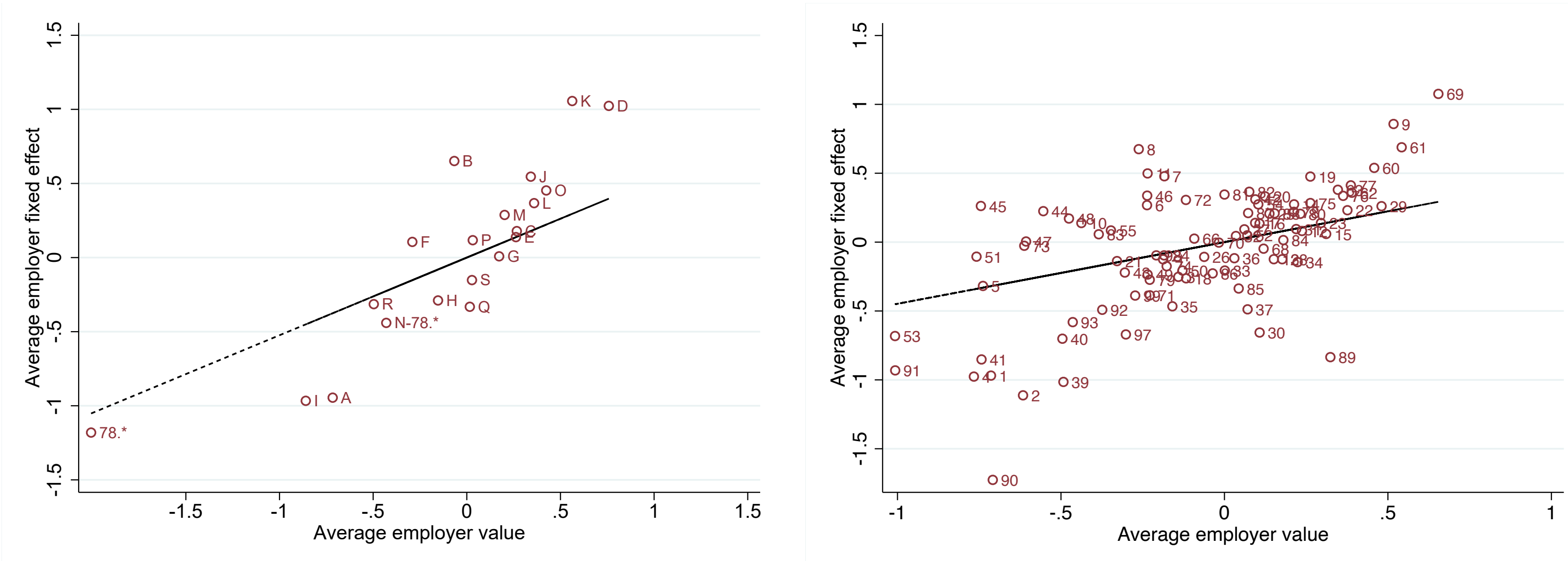
Figure 1: Relationship between Employer Fixed Effects and Employer Values



Notes: Each hollow circle in the figure shows studentized employer fixed effects and values averaged within 1 percent bins of the employer value distribution. The line of best fit shows the slope of the relationship between employer fixed effects and values, estimated on employer-level data. The dotted lines show one standard deviation bands of the employer fixed effect distribution. Estimates shown in the figure are based on 2010–2017 BeH data.

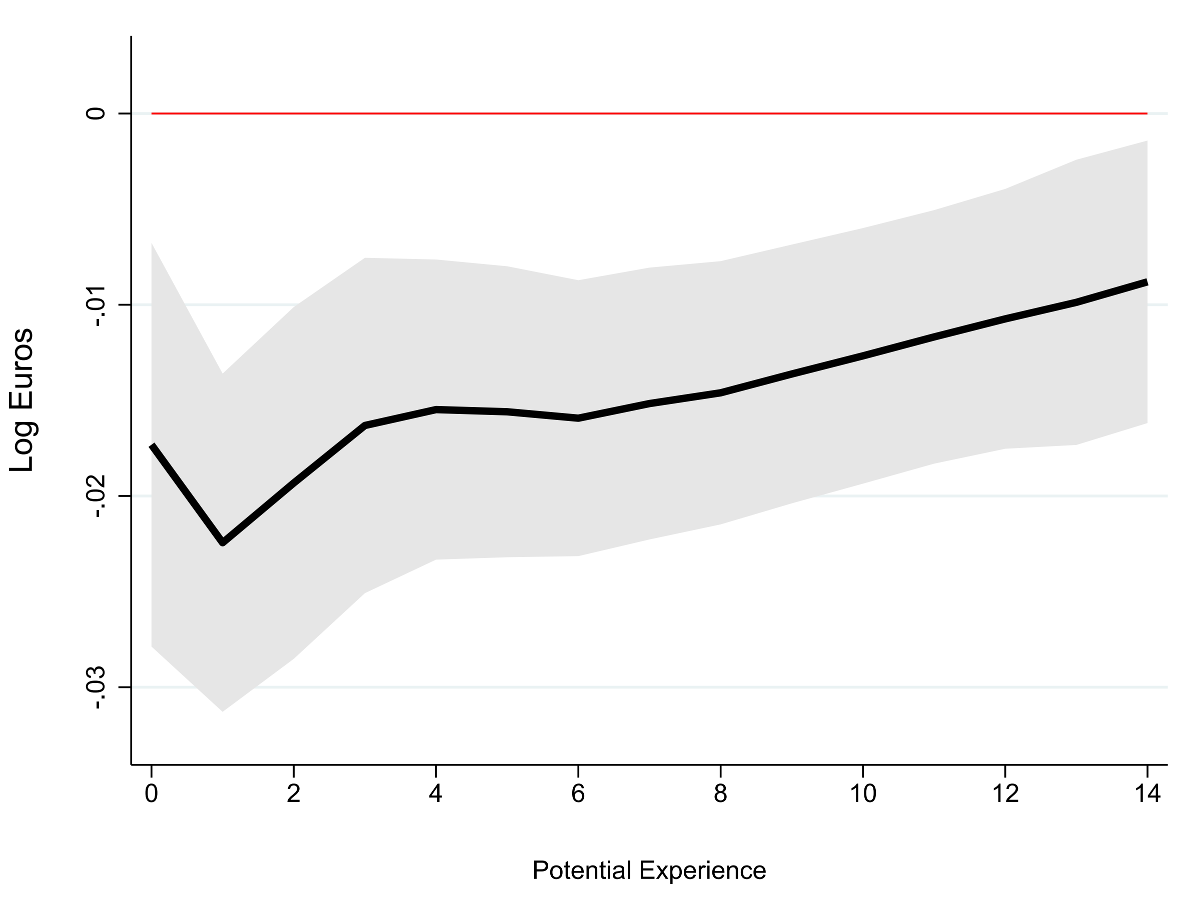
Figure 2: Employer Fixed Effects and Values within Sectors and Occupations

A: Sector **B: Occupation**



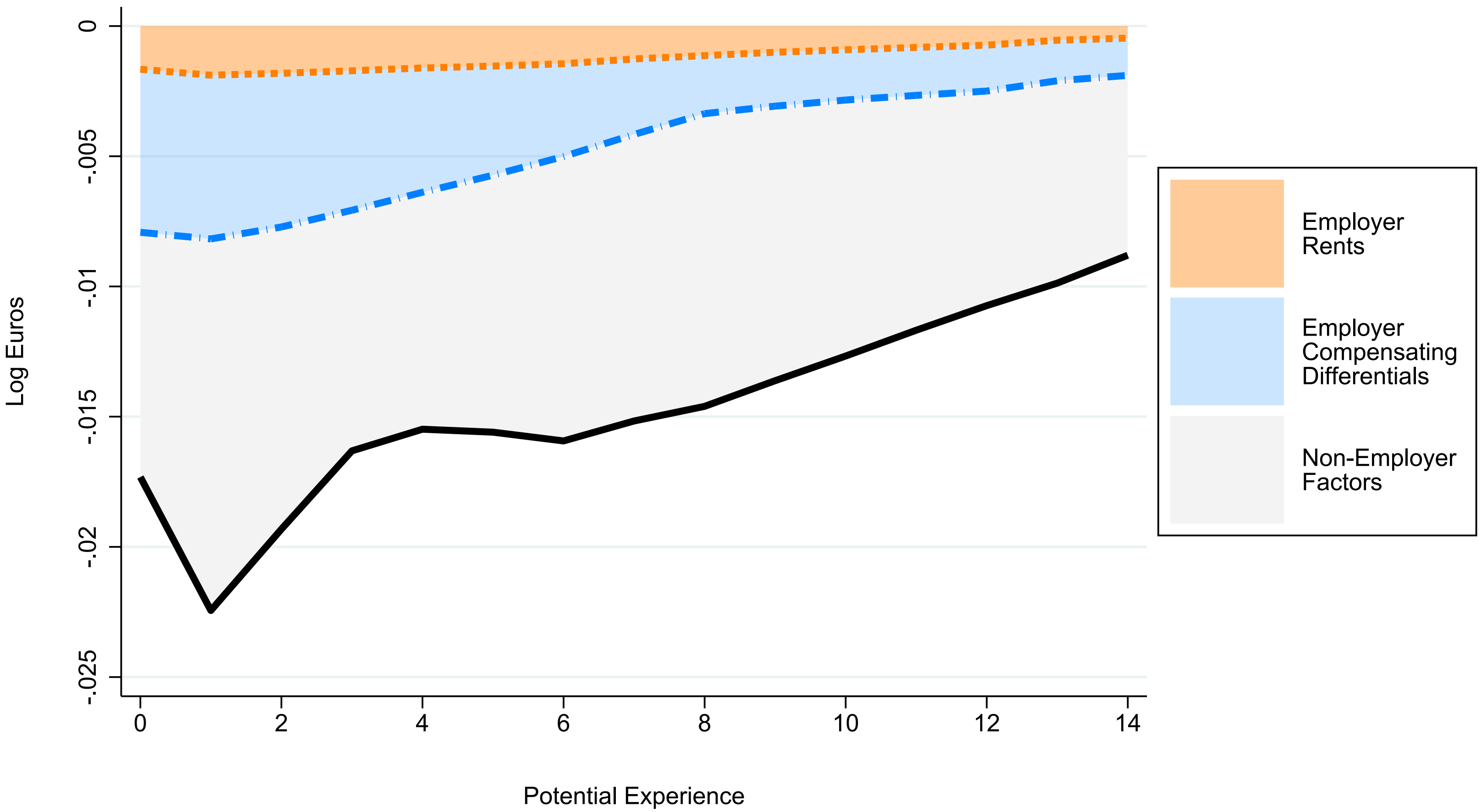
Notes: This figure bins studentized employer fixed effects and values by sector and two-digit occupation. Occupation estimates are constructed by weighting employer-level statistics by the relevant occupation share for each employer. The line of best fit shows the slope of the relationship between employer fixed effects and values, estimated on employer-level data. The top three and bottom three sectors by compensating differentials are, respectively, K: finance and insurance; B: mining and quarrying; D: electricity, gas, steam, and air conditioning supply; Q: human health and social work; I: accommodation and food service; A: agriculture, forestry, fishing. The top five and bottom five occupations by compensating differentials are, respectively 8: mineral, oil, natural gas quarries; 69: bank specialists, insurance representatives; 9: mineral preparers; 11: building material makers; 45: carpenters, roofers, scaffolders; 30: precision fitters; 39: bakery goods makers, confectioners (pastry); 2: animal breeders and fishermen; 89: ministers of religion; 90: body care occupations. See Appendix F for information on all industries and occupations. Sector classifications are based on the 2008 Industrial Classification of Economic Activities (WZ08) standard. Occupation classifications are based on the 1988 Classification of Occupations (KldB88) standard. Estimates shown in the figure are based on 2010–2017 BeH data.

Figure 3: The Effect of Unemployment Rate at Entry on Early Career Earnings



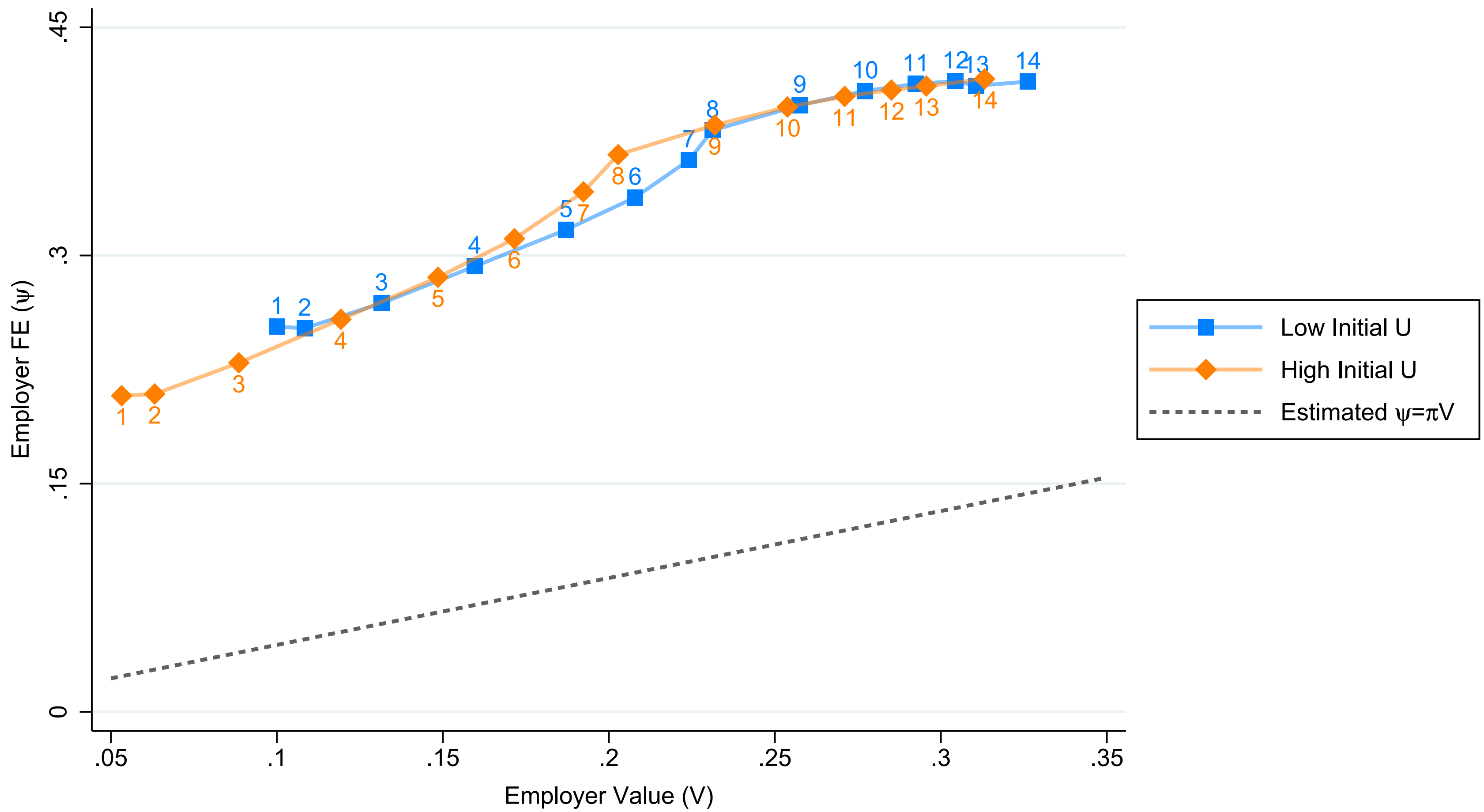
Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). All estimated coefficients are in log earnings units. The specification is estimated on 4,500,045 individuals who are followed for all years in which they are working in a full-time annual dominant job for an employer that has an estimated fixed effect and value. The 95 percent confidence intervals are represented by the gray area, with standard errors clustered at the state-of-entry level. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable.

Figure 4: Decomposing Early Career Earnings Losses



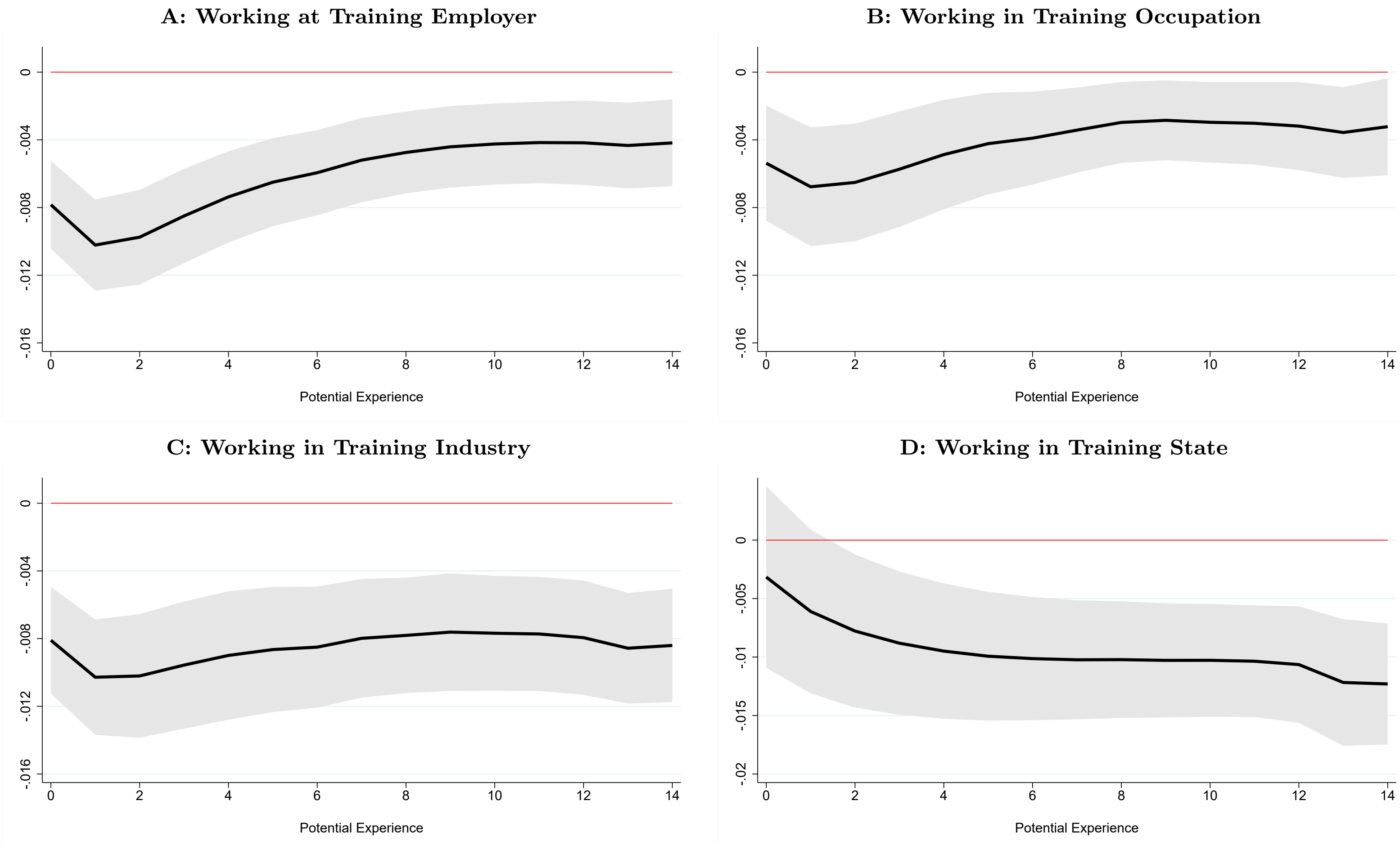
Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). All estimated coefficients are in log earnings units. Each specification is estimated on 4,500,045 individuals who are followed for all years in which they are working in a full-time annual dominant job for an employer that has an estimated fixed effect and value. The black solid line is based on employment in full-time annual dominant jobs and replicates Figure 3, using log earnings as the outcome in Equation (4). The blue dash-dotted line uses Employer FE (ψ_j) as the outcome in Equation (4). The short-dashed orange line uses Rents ($\hat{\pi}V_j$) as the outcome in Equation (4). Separate estimates of each component in this figure that include standard errors can be seen in Figure D1 of the Appendix. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable.

Figure 5: The Early Career Job Ladder in $\psi - V$ Space



Notes: The dashed line shows the relationship estimated in Equation (3) using studentized AKM employer effects and values. Labeled numbers indicate potential experience year. See Section 5.3 for details.

Figure 6: The Effect of Unemployment Rate at Entry on Early Career Mobility



Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). Each specification is estimated on 4,500,045 individuals who are followed for all years in which they are working in a full-time annual dominant job for an employer that has an estimated fixed effect and value. The 95 percent confidence intervals are represented by the shaded gray areas, with standard errors clustered at the state-of-entry level. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable.

Table 1: Compensating Differentials in Employer Earnings Premia

	Germany		U.S., Sorkin (2018)
	(1)	(2)	(3)
	2003–2010	2010–2017	2000–2008
$R^2(\psi_j, V_j)$	0.158	0.200	0.295
Number of employers	225,084	235,871	476,000
Number of worker moves	32,163,037	38,976,381	210,453,000
	Share of compensating differentials explained by observed factors		
State	0.185	0.158	0.077
County	0.203	0.182	0.150
Sector	0.121	0.079	0.297
Industry	0.220	0.159	0.445
County by industry	0.544	0.471	—

Notes: The top panel shows the R^2 from the regression of AKM employer fixed effects (ψ_j) on values (V_j). $1 - R^2$ is the variation in AKM employer fixed effects attributable to compensating differentials. Employers are included in the sample if they are part of the largest strongly connected set. Strong connectivity in columns (1) and (2) is defined inclusive of EN mobility, whereas strong connectivity in column (3) is defined based only on EE mobility. The count of worker moves in columns (1), (2), and (3) combines both EE and EN moves. The lower panel regresses the estimated compensating differentials, which are residuals from Equation (3), on different fixed effects and reports the R^2 from each of those regressions. Counties in Germany are defined by administrative units known as Kreise, which are approximately equivalent to U.S. counties. There are 16 states and 401 Kreise in Germany.

Table 2: Summary Statistics

Variable	A: Entrant Characteristics
German national share	0.949
Female share	0.45
Age in years at labor market entry	21.46
Lower–level secondary school share	0.806
Higher-level secondary school share	0.194
Number of unique individuals	6,303,695

	B: Post-Entry Outcomes, by Potential Experience				
Potential Experience Year	Log Earnings	Share Remaining at Training Employer	Share Retaining Training Occupation	Share Retaining Training Industry	Share Remaining in Training State
0	9.38	0.653	0.768	0.782	0.939
1	9.87	0.519	0.696	0.682	0.910
2	9.96	0.432	0.637	0.614	0.890
3	10.01	0.370	0.582	0.560	0.873
4	10.07	0.322	0.534	0.515	0.859
5	10.13	0.283	0.491	0.477	0.846
6	10.18	0.253	0.453	0.445	0.834
7	10.23	0.229	0.423	0.422	0.825
8	10.27	0.208	0.396	0.400	0.816
9	10.31	0.195	0.378	0.384	0.809
10	10.34	0.183	0.363	0.371	0.804
11	10.37	0.171	0.350	0.356	0.799
12	10.39	0.160	0.337	0.343	0.794
13	10.42	0.150	0.326	0.331	0.791
14	10.44	0.143	0.315	0.321	0.788
Mean across all years	10.04	0.347	0.533	0.527	0.859
Number of individual-years			23,058,886		
Number of unique individuals			4,500,045		

Notes: The sample in panel A includes all labor market entrants. Schooling levels refer to educational attainment prior to training. Higher-level secondary schooling refers to the attainment of an *Abitur* degree. Earnings are based on employment in full-time dominant jobs and are measured in 2015 euros. The sample in panel B includes individuals whose full-time dominant job is at an employer that has an estimated AKM fixed effect and value.

Table 3: Effect of Unemployment Rate at Entry on Placebo Training Outcomes

	Log Training Duration	Maintained Training Occupation	Obtained Training Certificate
U_{sc}	0.0011	-0.0019	0.0001
	(0.0017)	(0.0033)	(0.0010)
Dependent variable mean	6.739	0.808	0.872
N	6,303,695	6,303,695	6,303,695

Notes: This table shows the effect of the unemployment rate at entry on three different training outcomes. See Equation (5) for specification details. Standard errors shown in parentheses are clustered at the state-of-entry level. Training duration is measured in days. Workers are coded as having maintained their training occupation if their occupation at the start of training is the same as their occupation at the end of training. Workers are coded as having obtained a training certificate if, in spells subsequent to training, they are classified by employers as having successfully completed their apprenticeships.

Table 4: Percent PDV Earnings Losses from a One SD Increase in Unemployment Rate at Entry

	(1)	(2)	(3)	(4)	(5)
	Primary Sample	Trained in Low-Paying Occupations	Trained in High-Paying Occupations	Men	Women
Loss in earnings	5.59	5.56	5.45	6.11	4.44
	(1.33)	(1.14)	(1.40)	(1.44)	(1.11)
Due to employer-specific factors	1.79	1.52	1.89	1.70	1.89
	(0.48)	(0.36)	(0.55)	(0.49)	(0.47)
Due to rents	0.47	0.45	0.53	0.50	0.40
	(0.13)	(0.13)	(0.13)	(0.15)	(0.09)
Compensated for by non-pay amenities	1.32	1.07	1.36	1.20	1.49
	(0.36)	(0.24)	(0.43)	(0.35)	(0.41)
Due to non-employer factors	3.80	4.04	3.55	4.42	2.56
	(0.89)	(0.81)	(0.91)	(0.97)	(0.70)

Notes: This table shows the breakdown of the present discounted value of earnings losses induced by a one standard deviation ($\sigma_U = 3.80$) increase in the unemployment rate at entry—cumulated over 15 years. For example, in the primary sample, cohorts that face a one standard deviation higher unemployment rate at entry earn 5.59 percent less in their full-time dominant jobs over the first 15 years of their career relative to cohorts who do not face these adverse entry conditions. See Section 5.1 for how overall losses are estimated and Appendix D for how overall losses are divided into specific sub-components. Standard errors shown in parentheses are computed based on the linear combination of $\hat{\beta}_e$ coefficients obtained from Equation (6). The earnings associated with each level of potential experience and the standard deviation of the unemployment rate are treated as non-random for the purposes of this computation. The underlying standard errors for the $\hat{\beta}_e$ coefficients are clustered at the state-of-entry level.

Table 5: Cyclical Employment Dynamics at Low- and High-Amenity Employers

	(1) Growth Rate	(2) Hiring Rate	(3) Separation Rate
$\Delta\check{U}_{st}$	-0.576	-0.412	0.163
	(0.100)	(0.162)	(0.118)
High amenity	0.019	0.024	0.006
	(0.002)	(0.002)	(0.002)
$\Delta\check{U}_{st}$ × High amenity	0.475	0.390	-0.090
	(0.132)	(0.155)	(0.129)
Dependent variable mean	0.004	0.206	0.202
Industry fixed effects	Yes	Yes	Yes
N	2,989,589	2,989,589	2,989,589

Notes: This table shows the effect of the change in the state-year unemployment rate on employer-level growth rates, hiring rates, and separation rates. See Equation (7) for definitions. All regressions are weighted by mean employer size from year t through year $t-1$. Standard errors shown in parentheses are clustered at the state level.

Appendix for online publication

Appendix A Data

A.1 The Employee History File or Beschäftigtenhistorik (BeH)

The BeH data are linked employer-employee histories provided by the Institute for Employment Research (Institute für Arbeitsmarkt- und Berufsforschung, IAB). These data are based on the integrated notification procedure for unemployment insurance, health insurance, and old-age pensions (these three forms of social insurance are collectively considered social security in Germany), which came into effect as of January 1, 1973, and was extended to cover eastern Germany as of January 1, 1991 (see, for example, Wermter and Cramer (1988) and Bender et al. (1996)). These data cover all workers, including apprentices, but exclude civil servants, those in military service, the self-employed, and regular students (see Cramer (1985)). Employees in marginal part-time employment and unpaid family workers are included as of April 1, 1999.

Establishments in the BeH, which are assigned unique time-invariant identifiers, are either single-unit plants or groups of plants owned by the same firm that operate within the same municipality and industry. We refer to establishments in our data as employers.

Employers report the exact start and ending dates of an employment spell and annually confirm an existing employment spell, which makes it possible to track workers' careers on a daily basis. In addition, employers report spell-level information about earnings, full-time or part-time status, occupation, education, date of birth, gender, nationality, and place of residence. Employer-level information includes the place of business and industry classification.

We use the universe of employment spells of "regular" (defined below) full- and part-time workers who were aged 16 to 66 in the years 2002 through 2018.

Regular workers belong to one of the following BeH persons-group codes:

1. (101) employees subject to social security with no special features
2. (102) trainees/apprentices with no special features
3. (140) seamen
4. (141) trainees/apprentices in seafaring occupations with no special features
5. (143) maritime pilots

Interns, marginal part-time employees, employees in partial retirement, and persons performing basic or voluntary military service are not considered regular workers. For an overview of all persons groups in the BeH, refer to Ganzer et al. (2021) Table 8, pp. 111–112.

Appendix B Estimating Employer Value

Using matched employer-employee data from the BeH, we replicate the methodology developed in Sorkin (2018) to estimate a revealed preference estimate of workplace quality. The procedure has four distinct steps, and we discuss each of them in turn below.

B.1 Recording Job Changes

The BeH records employer-employee matches as spells that are measured with daily precision. When a worker is employed at multiple employers at the same time, we retain the spell associated with the highest daily wage (spell-level earnings divided by spell duration in days). After imposing this restriction and limiting our sample to full-time workers to retain consistency with the AKM effects, we track job changes as follows:[36]

1. Employer-to-employer (EE) moves are recorded when a job spell ends and the worker starts a new employment spell at a different employer. Provided that fewer than 31 days elapse between two adjacent employment spells, we classify the transition as an EE move.

2. Employer-to-nonemployment (EN) moves are recorded when a job spell ends and the worker then spends more than 31 days out of work. To avoid classifying retirement or death as an EN move, we remove transitions where a job spell ends and the worker is never subsequently observed returning to work at any employer.

3. Nonemployment-to-employment (NE) moves are recorded when a worker spends more than 31 days out of work and then takes a job.

B.2 Identifying Voluntary Job Changes

When EE and EN transitions are voluntary, and therefore endogenous, they are informative about workers' preferences. However, job changes caused by displacement are involuntary or exogenous and are not informative about workers' preferences. Lacking direct information about the voluntary or involuntary nature of a job change in administrative data, we exploit variation in the employer-level growth rate to estimate the probability that a given job change is voluntary.

We begin by computing the quarterly growth rate of each employer. As in Davis and Haltiwanger (1992), the growth rate for employer j in calendar quarter t is defined as

$$r_{j,t} = \frac{(\text{emp}_{j,t} - \text{emp}_{j,t-1})}{(\text{emp}_{j,t} + \text{emp}_{j,t-1})/2} \tag{9}$$

where $\text{emp}_{j,t}$ is the count of full-time employees at the end of the quarter. By definition, new employers have a growth rate of 2, whereas closing employers have a growth rate of –2. Next, we

[36] To address limited-mobility bias concerns, we impose a minimum employer size restriction of 10 full-time workers per year.

compute the EN and EE rate within 5 percentage point wide bins of the quarterly employer growth rate distribution, which we show in Figure B1. Notably, EE and EN rates are low and stable for growing employers. In contrast, EE and EN rates increase substantially at shrinking employers.

Following Sorkin (2018), we classify transitions out of growing employers as endogenous, up to an idiosyncratic shock, which we describe below. This assumption embeds the idea that, on average, workers who leave growing employers could have continued to work there if they wished to remain. Then, the benchmark probability that *any* EE transition is endogenous is the average EE transition probability for the set of growing employers. Similarly, the benchmark probability that *any* EN transition is endogenous is the average EN transition probability for the set of growing employers. At shrinking employers, the excess probability of an EE or EN transition over and above the voluntary transition probability is defined as the exogenous transition probability. NE transitions are always assumed to be endogenous.[37]

B.3 Imposing Connectivity Restrictions

As we will discuss in Section B.4.1, the revealed preference measure of employer value is based on estimating equations that can be taken to the data only for the set of worker moves that occur within a strongly connected set of employers. An employer is part of a strongly connected set if it both hires workers from *and* loses workers to other employers in the set. This restriction is related to the connectedness requirement needed to estimate AKM fixed effects. Employers are part of a connected set if they hire workers from *or* lose workers to other employers in the set. While Sorkin (2018) limits strong connectivity to employers linked only by EE flows, we expand the set to include employers linked by both EE flows and transitions of workers through nonemployment. This modification is fully consistent with the estimating equations in the Sorkin (2018) model that allow nonemployment to obtain its own relative value. Put differently, workers who make EN and NE transitions help to identify both the estimate of nonemployment value and estimates of employer values.

We treat nonemployment as a node in the graph of employers when obtaining the largest strongly connected set, which we do by using the graph algorithms provided by David Gleich in the Matlab `gaimc` library.[38] As shown in Table 1, there are 32 million worker moves across the nodes of the strongly connected set in the 2003–2010 estimation window and 39 million worker moves in the 2010–2017 estimation window. These statistics correspond to an average of 140–160 worker moves per node in each estimation window.

[37]In Sorkin (2018), workers receive offers randomly. Consequently, NE flows are informative about the offer distribution made by an employer. Estimating employer value requires that we observe non-null NE flows and we drop employers for which this condition is not met.

[38]See `https://www.mathworks.com/matlabcentral/fileexchange/24134-gaimc-graph-algorithms-in-matlab-code`.

B.4 Estimating the Structural Model

In the utility posting random job search model of Sorkin (2018), employer j makes a share of offers f_j and employs a share of workers g_j. Employers differ in their exogenous separation probabilities, δ_j and ρ_j. δ_j is the probability of a job destruction shock that forces a worker from employment to nonemployment (EN). ρ_j is the probability of a job reallocation shock that forces a worker from one employer to another (EE).[39] The forward-looking value of employer j is denoted by V_j^e and includes both pecuniary and non-pecuniary components. The forward-looking value of nonemployment is denoted by V^n.

In the model, workers draw an idiosyncratic shock from a type-I extreme value distribution in every period. This assumption allows movements between jobs to be driven by both the common component of employer value, V_j^e, and the idiosyncratic draw. The probability of receiving a job offer from another employer is λ_1, while the probability of receiving a job offer from a particular employer, j, is f_j. The goal of the estimation procedure we describe below is to recover an estimate of the V_j^e and V^n that rationalizes the observed pattern of endogenous EE and EN moves.

B.4.1 Flow-Relevant Values

Let $\boldsymbol{M}$ be a mobility matrix that records endogenous EE, EN, and NE moves. $\boldsymbol{M}$ is an $N^{\mathcal{E}} + 1 \times N^{\mathcal{E}} + 1$ matrix where $\mathcal{E}$ is the set of strongly connected employers of size $N^{\mathcal{E}}$, and nonemployment obtains its own row and column. m_{ij} represents the (i, j) entry in $\boldsymbol{M}$ and records the number of endogenous flows to employer i from employer j. Recall that all moves from growing employers and from nonemployment are endogenous, whereas the probability of an endogenous move from a shrinking employer is based on the growth rate at the time of separation, as in Figure B1. Thus, when employer j is growing, m_{ij} is simply the count of flows to employer i. When employer j is shrinking, m_{ij} is the count of flows to employer i weighted by the probability that those moves are endogenous.

Define $\exp(\tilde{V}_j)$, the exponentiated flow-relevant employer-level value, as

$$\exp(\tilde{V}_j) \equiv \frac{f_j \exp(V_j^e)}{g_j(1-\delta_j)(1-\rho_j)}. \tag{10}$$

The flow-relevant value is a reduced-form object that combines differences in the structural value, V_j^e, along with differences in the effective size and offer rate. In particular, employers that make more offers (f_j) have a higher flow-relevant value since they attract more workers. Similarly, employers with a larger effective size $(g_j(1-\delta_j)(1-\rho_j))$ have more workers depart for endogenous reasons and therefore have lower flow-relevant value.

Sorkin (2018) shows that the endogenous moves in the mobility matrix $\boldsymbol{M}$ can be reduced to a single linear restriction per employer. These employer-level restrictions can then be aggregated

[39] In estimation, these shock probabilities vary not at the employer level but only at the sector level.

such that

$$\boldsymbol{S}^{-1}\boldsymbol{M}\exp(\tilde{\boldsymbol{V}}) = \exp(\tilde{\boldsymbol{V}}). \tag{11}$$

In Equation (11), $\boldsymbol{S}$ is a diagonal matrix, with the i-th diagonal entry equal to $\sum_{j=1}^{N^{\mathcal{E}}+1} m_{ji}$, that is, the sum of all endogenous outflows from employer i. $\exp(\tilde{\boldsymbol{V}})$ is a vector of flow-relevant values for all employers and for nonemployment. This equation defines a high-dimensional function $\boldsymbol{S}^{-1}\boldsymbol{M}$ whose fixed point is $\exp(\tilde{\boldsymbol{V}})$.[40] Note that the strong connectivity requirement for estimating values arises from Equation (11). If there are no inflows into an employer, its row sum in $\boldsymbol{M}$ is zero and the flow-relevant value is mechanically zero. If there are no outflows from an employer, its column sum in $\boldsymbol{M}$ is zero and the flow-relevant value requires division by zero.

B.4.2 Estimation Loop

With an estimate of the flow-relevant values, one can obtain the structural values using the definition in Equation (10). However, this calculation requires an estimate of the offer distribution f_j. To estimate the structural values, we proceed using a loop that is set up as follows:

1. Initialize the model-implied endogenous EE and EN probabilities using observed EE and EN probabilities at expanding employers. Initialize $(V^n, \{V_j^e\}_{j=1}^{\mathcal{E}})$ using a uniform random vector of length $\mathcal{E} + 1$.

2. Construct $\boldsymbol{M}$ by classifying all observed EE and EN flows out of growing employers as endogenous and weighting the observed flows out of shrinking employers by their endogenous EE or EN probability. Compute δ and ρ using the exogenous transition probabilities out of shrinking employers.

3. With $\boldsymbol{M}$ and $\boldsymbol{S}$, obtain $\exp(\tilde{\boldsymbol{V}})$ by applying Equation (11) to an initial guess and iterating until convergence is attained.

4. Estimate f_j by doing a grid search for λ_1 to match the observed level of EE flows in the data. Details on the model equations used in these calculations are provided in Appendix G of Sorkin (2018). This step yields an estimate of $(V^n, \{V_j^e, f_j\}_{j=1}^{\mathcal{E}}, \lambda_1)$.

5. Using $(V^n, \{V_j^e, f_j\}_{j=1}^{\mathcal{E}}, \lambda_1)$ calculate the updated model-implied endogenous EE and EN probabilities. If the size-weighted correlation between the old and new estimates of $(V^n, \{V_j^e\}_{j=1}^{\mathcal{E}})$ is less than 0.999, then return to step 1 of the loop using the new estimates of $(V^n, \{V_j^e\}_{j=1}^{\mathcal{E}})$, If it is greater than or equal to 0.999, then stop.

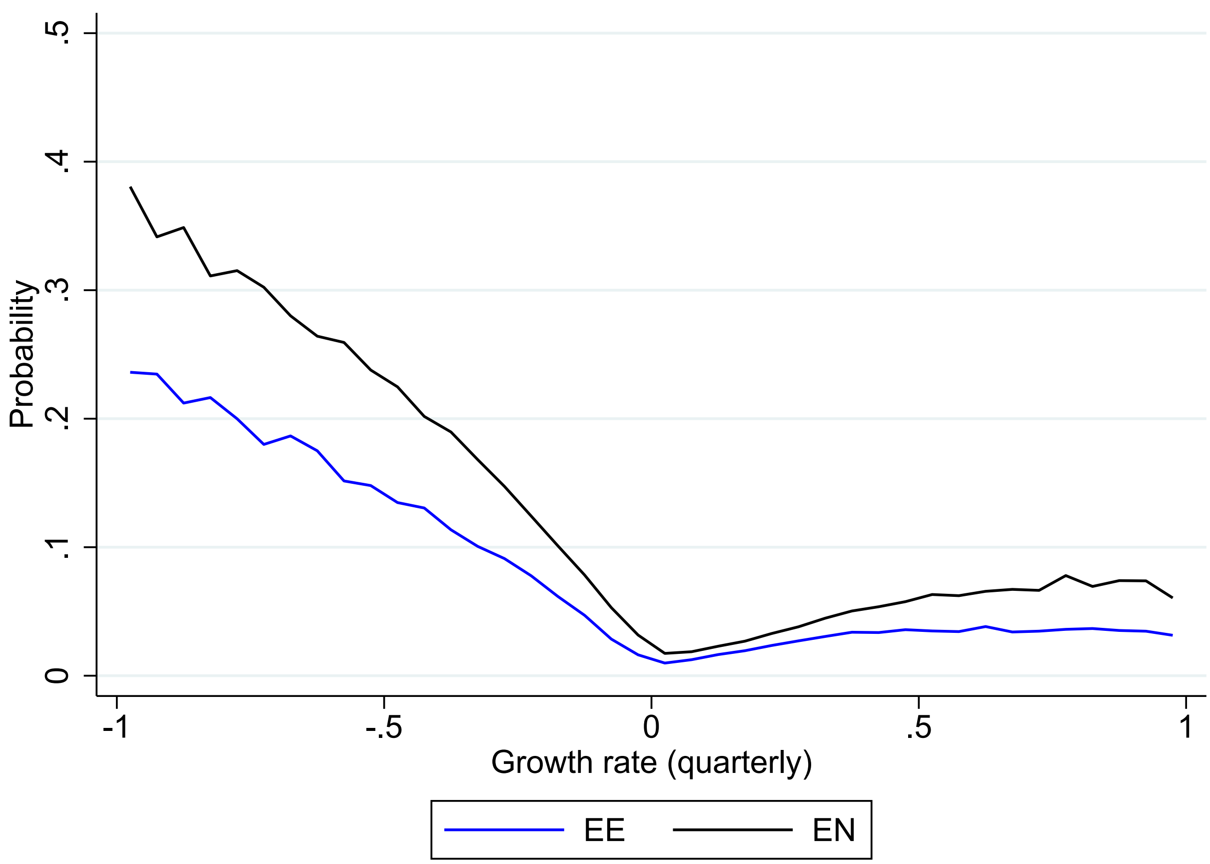
We implement this estimation routine for spells in the 2003–2010 time window and spells in the 2010–2017 time window separately to generate as many as two different estimates of value for each employer. Data from 2002 and 2018 are used to determine the source and destination of worker

[40] Sorkin (2018) shows that the top eigenvalue of $\boldsymbol{S}^{-1}\boldsymbol{M}$ is 1 and that $\exp(\tilde{\boldsymbol{V}})$ exists, is unique, and its elements all have the same sign.

inflows and outflows in 2003 and 2017, respectively. Consequently, there is no flow-level censoring of values estimated in the 2003–2010 and 2010–2017 windows.[41]

Table B1 shows model-based estimates of λ_1 (the probability of receiving a job offer), $\bar{\delta}$ (the average job displacement probability), and $\bar{\rho}$ (the average job reallocation probability) and compares the model-implied probabilities of endogenous EE and EN transitions with the same probabilities inferred from the data. The left column shows parameters for the 2003–2010 time window, while the right column shows parameters for the 2010–2017 time window.

Figure B1: Separation Hazard by Employer Growth Rate



Notes: This figure shows the separation hazard to nonemployment (EN) in black and the separation hazard to employment at a different employer (EE) in blue, averaged within 5 percentage point bins of the quarterly employer growth rate distribution. The separation hazards are censored at growth rates below –1 and above 1. Estimates shown in the figure are based on 2003–2010 BeH data.

[41] Employers that exist only in one of the two windows have a single value estimate.

Table B1: Parameter Estimates and Selected Moments

	Estimation window	
Parameter/Moment	2003-2010	2010-2017
λ_1	0.08	0.06
$\bar{\delta}$	0.03	0.06
$\bar{\rho}$	0.09	0.13
Probability of endogenous EE move - model	0.035	0.024
Probability of endogenous EE move - data	0.036	0.026
Probability of endogenous EN move - model	0.111	0.113
Probability of endogenous EN move - data	0.098	0.095

Notes: This table shows parameter estimates and compares model-implied moments to moments estimated from the data. All probabilities are annual. λ_1 is the probability of receiving a job offer. $\bar{\delta}$ is the probability of a job destruction shock averaged over all employers. $\bar{\rho}$ is the probability of a job reallocation shock averaged over all employers. Separations to nonemployment are considered in the data only if they are followed by subsequent re-employment within the relevant estimation window.

Appendix C Quantifying the Role of Measurement Error in Values

As discussed in Section 3.1, limited-mobility bias imparts noise to employer-level value estimates. Consequently, the dependent variable in Equation (3) is measured with error, which can cause attenuation bias in $\hat{\pi}$. Since rents are estimated as $\hat{\pi}V_j$, limited-mobility bias will understate rents and overstate compensating differentials. The extent to which this bias is quantitatively meaningful ultimately depends on the variance of estimation-induced noise in the values. In this section, we show that the bias attenuates $\hat{\pi}$ by less than 4 percent. This result comes from the fact that we effectively diminish estimation-induced noise by accumulating many worker moves per employer through a minimum firm full-time size restriction and the use of an eight-year long panel length.

C.1 Split-Sample Instrumental Variables Approach

To quantify the extent of attenuation bias in $\hat{\pi}$, we use a split-sample instrumental variables (IV) approach. We start by randomly splitting the set of worker moves into two non-overlapping samples. We then estimate values separately for each of the two random splits of the data. Denoting the (unobserved) true firm value by V_j^*, the employer value estimates derived from the two random splits of the data are:

$$V_j^1 = V_j^* + u_j^1 \tag{12}$$

$$V_j^2 = V_j^* + u_j^2, \tag{13}$$

where u_j^1 and u_j^2 are estimation-induced measurement errors that are assumed to be classical in nature (i.e., uncorrelated with V_j^*). Because the data are randomly partitioned into two independent samples of worker moves, u_j^1 and u_j^2 are orthogonal by construction. We can therefore use V_j^1 as an instrument for V_j^2 when estimating Equation (3) to purge attenuation bias from the estimate of π. In this framework, the ratio of the OLS-based estimate of π to the IV-based estimate quantifies the extent of attenuation bias.

Table C1 shows the results of this exercise separately for each of the two estimation windows 2003-2010 and 2010-2017. Starting with the first time window, in Column (1), we regress studentized AKM employer fixed effects on studentized values using V_j^2 as an instrument for V_j^1 and obtain an estimate of π of 0.567. Note that the sample size in this exercise is smaller than the total number of employers reported in Table 4 because of the split-sample approach. In particular, we consider only those employers that are strongly connected in each of the non-overlapping 50 percent random samples of worker moves. In Column (2), we reverse the order of the instruments, which is arbitrary, to obtain a second consistent estimate of π of 0.564. Finally, in column (3), we estimate Equation (3) by OLS using values derived from the full set of worker moves and obtain an estimate of π of 0.552. Comparing across the three columns, we see that the OLS-based estimate is within 97.2 (Column 3 divided by Column 1) percent and 97.8 (Column 3 divided by Column 2) percent of the two IV-based estimates. These results indicate that any attenuation effect driven by estimation error is ignorably small. The same conclusion emerges in the second time window: comparing Columns (4), (5), and (6), we find that the OLS-based estimate is within 96.3 percent and 97.8 percent of the IV-based estimates again confirming a very small degree of attenuation.

Taken together, the estimates in Table C1 provide evidence that our restriction that employers must have at least 10 full-time workers per year, our eight-year time windows, and our use of nonemployment as a node in the strongly connected set effectively mitigates the impact of limited-mobility bias in our estimates of rents and compensating differentials.

Table C1: Slope of the Employer-Pay-Value Relationship

	2003-2010			2010-2017		
	(1)	(2)	(3)	(4)	(5)	(6)
	IV-1	IV-2	OLS	IV-1	IV-2	OLS
$\hat{\pi}$	0.567	0.564	0.552	0.566	0.558	0.545
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	141,941	141,941	141,941	151,471	151,471	151,471

Notes: This table shows estimates of the slope coefficient in Equation (3) using studentized AKM employer effects and studentized values. The sample used in each estimation window is based on the graph of employers that are strongly connected in each of the non-overlapping 50 percent random samples of worker moves. Column (1) and (4) use V_j^2 as an instrument for V_j^1, while column (2) and (5) use V_j^1 as an instrument for V_j^2. Columns (3) and (6) use OLS and rely on values estimated using the full set of worker moves.

Appendix D Decomposition of Recession-Induced Losses

This appendix explains how we decompose recession-induced wage losses into three different components.

Consider a hypothetical sample of individuals who enter the labor market when unemployment rates are at their average level. Using the AKM decomposition, individual-level earnings can be decomposed as:

$$\log(y_{it}) = \alpha_i + \psi_{j(i,t)} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + r_{it}. \tag{14}$$

Taking expectations on both sides of Equation (1) in year t:

$$E\left[\log(y_{it})\right] = E\left[\alpha_i\right] + E\left[\psi_{j(i,t)}\right] + E\left[\boldsymbol{x}'_{it}\beta\right] + E\left[r_{it}\right]. \tag{15}$$

The average residual in Equation (15) in not zero because the expectation operator is taken over a sample of entrants in a specific year, rather than the population of worker-years from which the AKM decomposition is estimated. Next, define average earnings in year t if exactly the same group of individuals experienced a 1 percentage point increase in the unemployment rate at entry as

$$E\left[\log(y^R_{it})\right] = E\left[\alpha^R_i\right] + E\left[\psi^R_{j(i,t)}\right] + E\left[\boldsymbol{x}'^R_{it}\beta^R\right] + E\left[r^R_{it}\right]. \tag{16}$$

Relative to Equation (15), the person effects in Equation (16) are different because recession-induced earnings losses generate scarring effects that may not be fully removed in the eight-year time window over which the AKM decomposition is estimated. The employer effects are different due to recession-induced changes in worker-employer matching. The control variables and associated coefficients are different because they include calendar year effects, which capture the effect of aggregate shocks. The residual terms are different due to recession-induced changes in market-wide employer learning, unobserved human capital accumulation, and changes in the value of outside options (see, for example, the discussion about AKM residuals in Card et al. (2013)).

The average cost of recessionary entry on earnings in year t, $E\left[\log(y_{it})\right] - E\left[\log(y^R_{it})\right]$, can now be written as:

$$\underbrace{\beta^{\text{Earnings}}_t}_{\text{\% Earnings differential}} = \underbrace{E\left[\alpha_i + \boldsymbol{x}'_{it}\beta + r_{it}\right] - E\left[\alpha^R_i + \boldsymbol{x}'^R_{it}\beta^R + r^R_{it}\right]}_{\text{\% due to non-employer factors}} + \underbrace{E\left[\psi_{j(i,t)}\right] - E\left[\psi^R_{j(i,t)}\right]}_{\text{\% due to employer-specific factors}}. \tag{17}$$

Next, define

$$\beta^{\text{Non-employer}}_t = E\left[\alpha_i + \boldsymbol{x}'_{it}\beta + r_{it}\right] - E\left[\alpha^R_i + \boldsymbol{x}'^R_{it}\beta^R + r^R_{it}\right], \tag{18}$$

$$\beta^{\text{Employer}}_t = E\left[\psi_{j(i,t)}\right] - E\left[\psi^R_{j(i,t)}\right], \tag{19}$$

as the non-employer and employer-specific components of recession-induced earnings differentials in year t. Estimating our main specification (Equation (4)) using employer fixed effects ($\psi_{j(i,t)}$) on the left-hand-side provides us with $\left\{\hat{\beta}_0^{\text{Employer}}, \ldots, \hat{\beta}_8^{\text{Employer}}\right\}$.

Having defined recession-induced employer-specific losses, we now partition these losses into rents and compensating differentials using the decomposition in Equation (3). Recall that this decomposition splits employer fixed effects into rents, which are explained by employer value, and amenities, which are orthogonal to employer value. Taking expectations on both sides, year t employer effects for our hypothetical sample of individuals who enter the labor market when unemployment rates are at their average level are:

$$E\left[\psi_{j(i,t)}\right] = \pi E\left[V_{j(i,t)}\right] + E\left[\epsilon_{j(i,t)}\right]. \tag{20}$$

Employer effects for otherwise identical individuals who enter the labor market when unemployment rates are 1 percentage point higher are

$$E\left[\psi_{j(i,t)}^R\right] = \pi E\left[V_{j(i,t)}^R\right] + E\left[\epsilon_{j(i,t)}^R\right]. \tag{21}$$

Subtracting Equation (21) from Equation (20), the employer-specific pay reduction is

$$\beta_t^{\text{Employer}} = \underbrace{\pi\left(E\left[V_{j(i,t)}\right] - E\left[V_{j(i,t)}^R\right]\right)}_{\text{\% due to rents}} - \underbrace{\left(E\left[\epsilon_{j(i,t)}\right] + E\left[\epsilon_{j(i,t)}^R\right]\right)}_{\text{\% due to amenities}}. \tag{22}$$

Next, define

$$\beta_t^{\text{Rent}} = \pi\left(E\left[V_{j(i,t)}\right] - E\left[V_{j(i,t)}^R\right]\right), \tag{23}$$

$$\beta_t^{\text{Amenity}} = E\left[\epsilon_{j(i,t)}\right] - E\left[\epsilon_{j(i,t)}^R\right], \tag{24}$$

Combining Equations (17) and (22), we can write

$$\begin{aligned}\beta_t^{\text{Earnings}} &= \beta_t^{\text{Non-employer}} + \beta_t^{\text{Employer}} \\ &= \beta_t^{\text{Non-employer}} + \left(\beta_t^{\text{Rent}} - \beta_t^{\text{Amenity}}\right)\end{aligned} \tag{25}$$

Because $\beta_t^{\text{Earnings}}$,β_t^{Rent}, and β_t^{Amenity} are estimated directly, we can recover $\beta_t^{\text{Non-employer}}$ as a residual using Equation (25).

Finally, define the present value of earnings for the first nine years of potential experience as

$$PDV = \bar{y}_0 + \frac{\bar{y}_1}{(1+r)} + \cdots + \frac{\bar{y}_8}{(1+r)^8}, \tag{26}$$

where $\bar{y}_e$ represents average annual earnings in potential experience year e. The PDV of earnings for workers who face a 1 percentage point increase in the unemployment rate at entry is

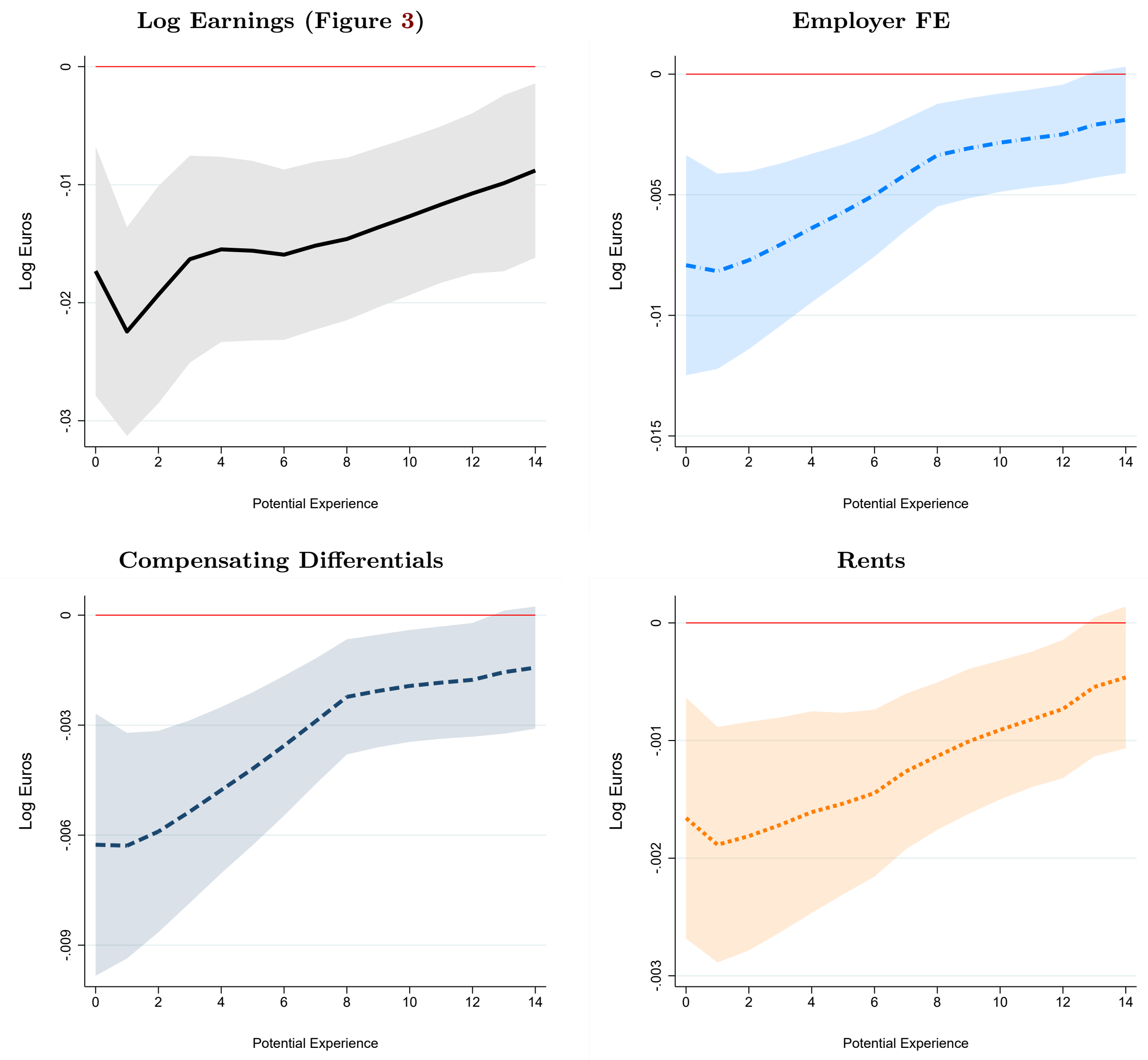
$$PDV^R = \bar{y}_0(1+\beta_0^{\text{Earnings}}) + \frac{\bar{y}_1(1+\beta_1^{\text{Earnings}})}{(1+r)} + \cdots + \frac{\bar{y}_{14}(1+\beta_{14}^{\text{Earnings}})}{(1+r)^{14}} \tag{27}$$

We use $\left\{\hat{\beta}_0^{\text{Earnings}}, \ldots, \hat{\beta}_{14}^{\text{Earnings}}\right\}$ to quantify the loss in the present value of earnings attributable to a 1 percentage point change in the unemployment rate. We then scale the resulting estimate by a one standard deviation increase in the unemployment rate, which reflects a typical recession. Similar calculations with $\left\{\hat{\beta}_0^{\text{Employer}}, \ldots, \hat{\beta}_{14}^{\text{Employer}}\right\}$, $\left\{\hat{\beta}_0^{\text{Rent}}, \ldots, \hat{\beta}_{14}^{\text{Rent}}\right\}$, $\left\{\hat{\beta}_0^{\text{Amenity}}, \ldots, \hat{\beta}_{14}^{\text{Amenity}}\right\}$, and $\left\{\hat{\beta}_0^{\text{Non-employer}}, \ldots, \hat{\beta}_{14}^{\text{Non-employer}}\right\}$ yield estimates of the loss in the PDV of earnings attributable to employer-specific factors, rents, amenities, and non-employer factors.

Appendix E Supplemental Analyses

E.1 Separated Recession-Induced Changes to Employer-Specific Pay, Compensating Differentials, and Rents (with Standard Errors)

Figure D1: The Effect of Unemployment Rate at Entry on Early Career Mobility



Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). Each specification is estimated on 4,500,045 individuals who are followed for all years in which they are working in a full-time annual dominant job for an employer that has an estimated fixed effect and value. The 95 percent confidence intervals are represented by the shaded areas, with standard errors clustered at the state-of-entry level. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable. Note the difference in scales. Estimated coefficients on Compensating Differentials and Rents add up to estimated coefficients on Employer FE for a given potential experience year. A decomposition of the coefficients on log earnings (top left) into its constituent components (the other panels of this figure) can be seen in Figure 4 of the main text.

E.2 Comparing Full-Time Dominant Job Earnings with Total Earnings

Due to the sample restrictions required by the AKM decomposition and the Sorkin (2018) model, we analyze full-time dominant jobs (FTDJ) within a strongly connected set in the main text.[42] In this section, we compare our earnings results from the restricted FTDJ sample with results from an unrestricted sample that pools earnings across all jobs held by a worker in a given year. We show that the results are not qualitatively different across these samples.

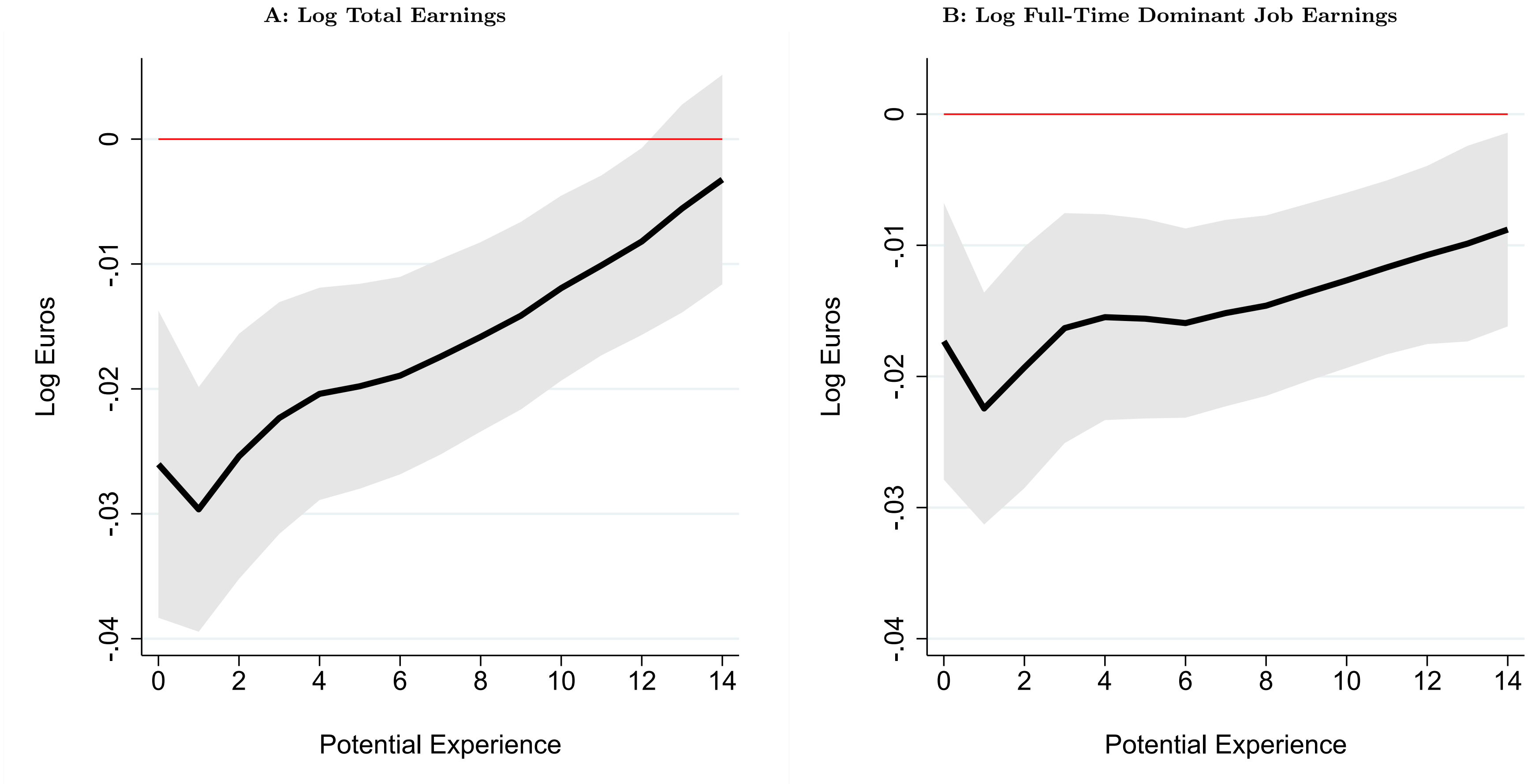
Table D1: Percent PDV Earnings Losses from a One SD Increase in Unemployment Rate at Entry

	(1) Primary Sample	(2) Trained in Low-Paying Occupations	(3) Trained in High-Paying Occupations	(4) Men	(5) Women
Loss in total earnings	6.36	6.76	5.80	7.57	4.95
	(1.48)	(1.42)	(1.47)	(1.54)	(1.40)
Loss in FTDJ earnings	5.59	5.56	5.44	6.11	4.44
	(1.33)	(1.14)	(1.40)	(1.44)	(1.11)

Notes: This table shows the breakdown of the present discounted value of earnings losses induced by a one standard deviation ($\sigma_U = 3.80$) increase in the unemployment rate at entry—cumulated over 15 years. For example, in the primary sample, cohorts that face a one standard deviation higher unemployment rate at entry earn 6.36 percent less over the first 15 years of their career relative to cohorts who do not face these adverse entry conditions. The second row of this table is the same as the first row in Table 4. See Section 5.1 for how overall losses are estimated. Standard errors shown in parentheses are computed based on the linear combination of $\hat{\beta}_e$ coefficients obtained from Equation (6). The earnings associated with each level of potential experience and the standard deviation of the unemployment rate are treated as non-random for the purposes of this computation. The underlying standard errors for the $\hat{\beta}_e$ coefficients are clustered at the state-of-entry level.

[42] Recall that employer values are computed using full-time jobs within the largest strongly connected set of employers, where each employer has 10 or more full-time workers per year.

Figure D2: The Effect of Unemployment Rate at Entry on Early Career Earnings Trajectories

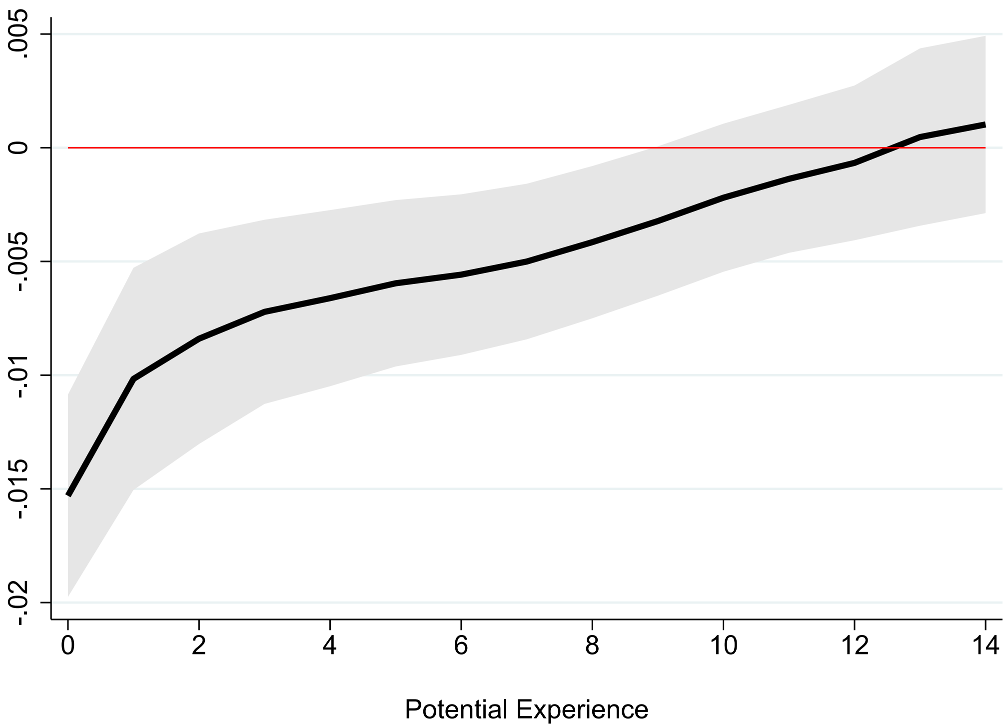


Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). All estimated coefficients are in log earnings units. The specification for the left panel is estimated on 6,303,695 individuals who are followed for all years in which they work. The specification for the right panel is estimated on 4,500,045 individuals who are followed for all years in which they work in a full-time annual dominant job for an employer that has an estimated fixed effect and value. The 95 percent confidence intervals are represented by the gray area, with standard errors clustered at the state level. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable.

E.3 Recession-Induced Changes in Employment

In this section we study the impact of higher unemployment rates at entry on early-career employment propensities. To do this, we estimate Equation (4) using an outcome of full-year nonemployment, which is defined as zero earnings over the course of a calendar year.[43] We plot the β_e coefficients from this regression in Figure D3, which shows a pattern similar to the earnings trajectories. Workers are about 1.5 percentage points more likely to experience full-year nonemployment at entry. This effect is halved in three years and slowly decays to zero after about 10 years of potential experience.

Figure D3: The Effect of Unemployment Rate at Entry on Employment



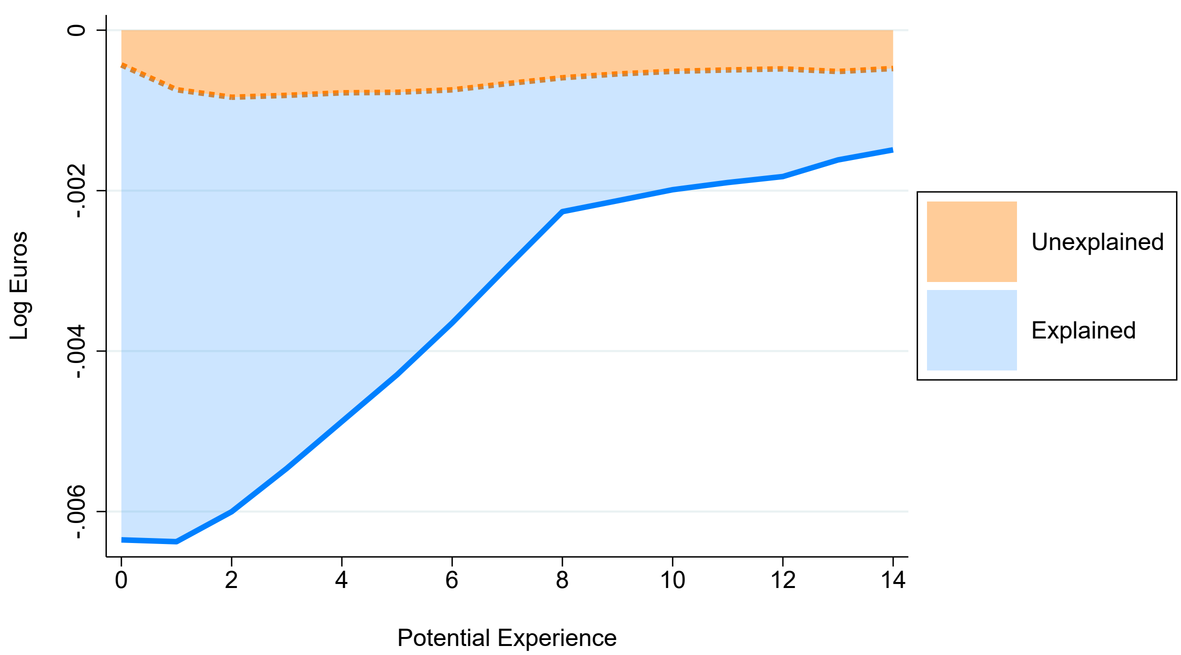
Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). The specification is estimated on 6,303,695 individuals who are followed for all years after they complete vocational training. The 95 percent confidence intervals are represented by the shaded areas, with standard errors clustered at the state level. Controls included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable.

[43] In the year of entry, this variable is based on earnings in non-training employment spells.

E.4 The Role of Industry, Occupation, and Location in Explaining Recession-Induced Compensating Differentials

As described in the main text, we assess how important industry, occupation, and location are in explaining our headline finding by regressing our compensating differential on industry by county fixed effects, then using the residual as the outcome in a version of Equation (4) that includes current occupation fixed effects. Figure D4, below, compares the estimated $\hat{\beta}_e$ from this regression with the estimated $\hat{\beta}_e$ from estimating Equation (4) with non-residualized compensating differentials as the outcome, without current-occupation fixed effects. It is both a visual illustration of our finding that a majority of the amenity buffer received by recessionary entrants is explained by industry, location, and occupation and an illustration that this buffer is most operative in the first eight years of their careers.

Figure D4: The Role of Industry, Occupation, and Location in Explaining Recession-Induced Compensating Differential Losses (Amenity Gains)



Notes: Lines connect coefficients $\hat{\beta}_e$, estimated by Equation (4). The specification is estimated on 4,500,045 individuals who are followed for all years in which they are working in a full-time annual dominant job for an employer that has an estimated fixed effect and value. Controls always included are potential experience fixed effects, year fixed effects, year of entry fixed effects, month of entry fixed effects, training occupation fixed effects, state of training fixed effects, age at labor market entry fixed effects, level of pre-training education fixed effects, a German national indicator variable, and a female indicator variable. The short-dashed, orange line represents $\hat{\beta}_e$ estimates where the outcome is compensating differentials residualized with respect to industry by county fixed effects and where controls also include current occupation fixed effects. The solid, blue line represents $\hat{\beta}_e$ where the outcome is compensating differentials.

Appendix F Employer Effects Binned by Sector and Occupation

Table E1: Employer Effects Binned within Sector

Sector	Value	Employer Fixed Effect	Rent	Compensating Differential
K: Financial and insurance activities	0.563	1.056	0.295	0.761
B: Mining and quarrying	-0.067	0.652	-0.035	0.687
D: Electricity, gas, steam and air conditioning supply	0.758	1.024	0.398	0.626
J: Information and communication	0.342	0.546	0.179	0.367
F: Construction	-0.291	0.106	-0.153	0.258
O: Public administration and defense	0.424	0.453	0.222	0.231
M: Professional, scientific and technical activities	0.202	0.288	0.106	0.182
L: Real estate activities	0.359	0.367	0.188	0.179
P: Education	0.032	0.117	0.017	0.101
C: Manufacturing	0.267	0.179	0.140	0.039
E: Water supply; sewerage, waste management and remediation	0.262	0.138	0.138	0.000
R: Arts, entertainment and recreation	-0.497	-0.314	-0.260	-0.054
G: Wholesale and retail trade; repair of motor vehicles	0.173	0.008	0.091	-0.082
78.*: Employment activities (normally part of N)	-2.006	-1.181	-1.052	-0.129
S: Other service activities	0.028	-0.152	0.015	-0.166
H: Transportation and storage	-0.154	-0.289	-0.081	-0.209
N-78.*: Administrative and support service activities	-0.430	-0.441	-0.226	-0.215
Q: Human health and social work activities	0.016	-0.332	0.008	-0.340
I: Accommodation and food service activities	-0.860	-0.966	-0.451	-0.516
A: Agriculture, forestry and fishing	-0.716	-0.945	-0.376	-0.570

Notes: This table averages studentized employer value, studentized employer fixed effects, rents and compensating differentials by sector. Sectors are sorted on the basis of compensating differentials. Sector classifications are based on the 2008 Industrial Classification of Economic Activities (WZ08) standard. Industry 78* refers to "employment activities," which includes businesses that provide workers for hire to other businesses, that is, outsourcing services. This industry is normally absorbed in sector N, but we disaggregate it because it has very low value relative to other sectors. Estimates are based on 2010–2017 BeH data.

Table E2: Employer Effects Binned within Occupation

	Two-Digit Occupation	Value	Employer Fixed Effect	Rent	Compensating Differential
8:	Mineral, oil, natural gas quarries	-0.262	0.675	-0.117	0.792
69:	Bank specialists, insurance representatives	0.654	1.076	0.293	0.783
9:	Mineral preparers	0.517	0.858	0.231	0.626
11:	Building material makers	-0.235	0.499	-0.105	0.604
45:	Carpenters, roofers, scaffolders	-0.745	0.262	-0.333	0.596
7:	Miners	-0.184	0.478	-0.082	0.560
44:	Bricklayers, concrete workers	-0.554	0.225	-0.248	0.473
61:	Chemists, physicists, mathematicians	0.542	0.688	0.243	0.446
46:	Road makers, civil engineering workers	-0.236	0.337	-0.106	0.443
48:	Building finishers	-0.476	0.171	-0.213	0.384
6:	Forestry and hunting occupations	-0.237	0.268	-0.106	0.374
72:	Water and air transport occupations	-0.118	0.306	-0.053	0.359
19:	Metal producers, rollers	0.263	0.476	0.118	0.358
81:	Legal and related business associate professionals	0.000	0.345	0.000	0.345
10:	Stone preparers	-0.438	0.138	-0.196	0.334
60:	Engineers	0.458	0.539	0.205	0.334
82:	Journalists, interpreters, librarians	0.076	0.366	0.034	0.332
20:	Moulders, mould casters	0.124	0.332	0.056	0.277
47:	Building laborer, general	-0.607	0.004	-0.272	0.276
42:	Beverage makers, luxury food makers	0.094	0.311	0.042	0.268
73:	Communication occupations	-0.612	-0.026	-0.274	0.248
55:	Disabled workers	-0.347	0.085	-0.155	0.240
77:	Accountants, data processing specialists	0.387	0.412	0.173	0.239
51:	Painters, lacquerers and related occupations	-0.758	-0.106	-0.339	0.234
83:	Artists	-0.384	0.057	-0.172	0.229
54:	Machinists and related occupations	0.103	0.274	0.046	0.228
63:	Technical specialists	0.347	0.380	0.155	0.225
62:	Technicians	0.389	0.359	0.174	0.184
14:	Chemical workers	0.213	0.274	0.095	0.179
87:	Teachers	0.073	0.211	0.032	0.179
76:	Members of parliament, senior government officials	0.363	0.336	0.162	0.173
75:	Management consultants, organizers, chartered accountants	0.263	0.284	0.118	0.166
25:	Smiths	0.138	0.206	0.062	0.145
88:	Humanities specialists, scientists	0.153	0.209	0.069	0.140
78:	Office specialists; office auxiliary workers	0.213	0.220	0.095	0.125
80:	Protective services workers	0.232	0.206	0.104	0.102
17:	Printer	0.094	0.139	0.042	0.097
16:	Paper makers	0.107	0.135	0.048	0.087
66:	Rehabilitants	-0.092	0.025	-0.041	0.067
27:	Locksmiths	0.061	0.093	0.027	0.066
22:	Metal moulders (metal-cutting deformation)	0.376	0.232	0.168	0.063
29:	Toolmakers	0.481	0.261	0.215	0.046
32:	Assemblers and metal workers (no further specification)	0.035	0.044	0.016	0.029
52:	Goods examiner, dispatchers	0.070	0.049	0.031	0.018
5:	Gardeners	-0.739	-0.318	-0.330	0.012
21:	Metal moulders (non-cutting deformation)	-0.329	-0.138	-0.147	0.009
23:	Metal surface workers, metal heat-treating-plant operators	0.295	0.139	0.132	0.007
70:	Other services agents and related occupations	-0.017	-0.003	-0.008	0.004
98:	Workforce (job seekers) with unspecified occupation	-0.208	-0.096	-0.093	-0.003
31:	Electricians	0.219	0.095	0.098	-0.003

	Two-Digit Occupation	Value	AKM Pay Premium	Rent	Compensating Differential
24:	Metal connectors	-0.185	-0.096	-0.083	-0.014
12:	Ceramics workers	0.237	0.081	0.106	-0.025
-1:	Missing occupation	-0.188	-0.125	-0.084	-0.041
84:	Physicians, pharmacists	0.180	0.015	0.081	-0.066
26:	Sheet metal workers	-0.062	-0.107	-0.028	-0.080
15:	Plastics processors	0.311	0.059	0.139	-0.080
43:	Other nutrition occupations	-0.305	-0.221	-0.136	-0.085
74:	Warehouse managers, stores, transport workers	-0.177	-0.175	-0.079	-0.096
68:	Wholesale and retail trade	0.120	-0.048	0.054	-0.101
49:	Room equippers, upholsterers	-0.235	-0.235	-0.105	-0.130
36:	Textile finisher	0.030	-0.117	0.014	-0.130
50:	Carpenters, model makers	-0.128	-0.206	-0.057	-0.149
79:	Watchpersons and related workers	-0.229	-0.273	-0.102	-0.171
3:	Managers, advisors in agriculture and animal breeding	-0.141	-0.252	-0.063	-0.189
13:	Glass makers	0.151	-0.124	0.068	-0.192
28:	Mechanics	0.177	-0.124	0.079	-0.203
33:	Spinners	0.001	-0.206	0.001	-0.207
18:	Wood preparers, wood products makers	-0.117	-0.263	-0.052	-0.210
86:	Social work associate professionals	-0.036	-0.227	-0.016	-0.211
53:	Assistants (no further specification)	-1.008	-0.682	-0.451	-0.231
34:	Textile makers	0.224	-0.145	0.100	-0.245
99:	Workforce not further specified	-0.273	-0.388	-0.122	-0.266
71:	Surface transport occupations	-0.228	-0.386	-0.102	-0.284
92:	Housekeeping occupations	-0.374	-0.491	-0.167	-0.324
85:	Other health occupations	0.044	-0.337	0.019	-0.356
93:	Cleaning occupations	-0.464	-0.581	-0.208	-0.373
35:	Textile processor	-0.159	-0.466	-0.071	-0.395
40:	Butchers, fish processing operatives	-0.496	-0.701	-0.222	-0.479
91:	Attending on guests occupations	-1.007	-0.931	-0.451	-0.481
41:	Food preparers	-0.743	-0.852	-0.332	-0.519
37:	Leather makers, leather and skin processing operatives	0.071	-0.488	0.032	-0.520
97:	Non-agricultural family assistants, n.e.c.	-0.301	-0.670	-0.135	-0.535
4:	Land workers, animal keeper	-0.766	-0.976	-0.343	-0.633
1:	Farmers	-0.714	-0.969	-0.319	-0.650
30:	Precision fitters	0.108	-0.656	0.048	-0.704
39:	Bakery goods makers, confectioners (pastry)	-0.492	-1.015	-0.220	-0.795
2:	Animal breeders; fishermen	-0.616	-1.112	-0.276	-0.837
89:	Ministers of religion	0.324	-0.835	0.145	-0.980
90:	Body care occupations	-0.709	-1.726	-0.317	-1.409

Notes: This table averages studentized employer value, studentized AKM employer fixed effects, rents, and compensating differentials by two-digit occupation, sorted by compensating differentials. Occupation estimates are constructed by weighting employer-level statistics by the relevant occupation share for each employer. Occupation classifications are based on the 1988 Classification of Occupations (KldB88) standard. Estimates shown in the figure are based on 2010–2017 BeH data.

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