Non-Wage Job Values and Implications for Inequality *

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Abstract

I study inequality in job values, both in terms of wages and non-wage values, in Austria over the period 1996 to 2011. Identification of non-wage job values is based on patterns of worker flows between firms and wage differentials. Intuitively, firms with high non-wage value attract workers without paying a wage premium. Looking at the distribution of job value among workers, I find a positive correlation between wage and non-wage value. Inequality in job value is thus greater than wage inequality. Job value inequality increases between 1996 and 2011, although wage inequality remains constant. I show that this is due to a change in the relationship between the part of wage that is systematically attributable to a firm, the firm wage premium, and the non-wage value that firms offer. Between 1996 and 2003, firms' wage premium and their non-wage value are negatively correlated, reflecting compensating differentials attenuating job value inequality. In the 2004 to 2011 period, however, this correlation becomes positive. I show that compensating differentials disappear because providing non-wage value becomes cheaper over time for firms initially offering low non-wage value. The disappearance of compensating differentials comes with an increase in the dispersion of job value offered by firms. Using a model of monopsonistic competition, I provide evidence that this is caused by two developments over time: first, workers respond less to firms' job value offers, reflecting a decline in the elasticity of labor supply. Second, labor supplied to firms offering low value increases disproportionately because of labor immigration.

Keywords: Inequality, Amenities, Worker heterogeneity, Firm heterogeneity, On-the-job search, Wage dispersion, Matched employer–employee data

JEL Classification Numbers: J31, J32, E24

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1 Introduction

Workers derive utility from their job's wage, and from its non-wage value. Recent experimental evidence shows that workers have high valuation for some non-wage characteristics, for example, schedule flexibility or the opportunity to telecommute (Mas and Pallais, 2017; Maestas et al., 2018; Wiswall and Zafar, 2018). Taber and Vejlin (2020) estimate that only half of the variance of utility workers derive from jobs comes from wage, while the other half is borne by non-wage values. Understanding inequality in workers' well-being thus requires consideration of both, wage and non-wage values of jobs.[1]

While a blossoming literature discusses wage inequality (see Acemoglu and Autor (2011) and Card et al. (2018) for detailed reviews), there is remarkably little empirical evidence on inequality in non-wage values. Maestas et al. (2018) show that non-wage characteristics tend to be worse in low-wage jobs, therefore exacerbating inequality in job value compared to wage inequality.[2] Hamermesh (1999) and Pierce (2001) show that inequality in jobs' fringe benefits and risk of injury grew stronger than wage inequality in the US in the 1980s and 1990s. While these studies document interesting patterns with respect to the *subset* of non-wage characteristics they consider, it remains an open question how labor market inequality is affected if *all* non-wage characteristics of jobs are taken into account.[3] Knowing the value of *all* non-wage characteristics of jobs, however, is necessary for statements about inequality in workers' overall well-being.

In this article I address this question by estimating the total non-wage value each worker has at his job. Combining wage and non-wage value allows me to study the evolution of inequality in total job value, and to compare it to the evolution of wage inequality. In my framework, workers consider wage and non-wage value when comparing job offers. I identify non-wage value as the residual that explains observed job choices after accounting for wage. My definition of non-wage value thus, by construction, captures the full set of workplace characteristics that contribute to workers' utility.

My analyses are based on Austria, a labor market more comparable to the US than others in Europe, for example, regarding the unemployment rate and labor turnover (Stiglbauer et al., 2003). I use employer-to-employer transitions in Austrian administrative data between

[1] *"The ultimate desideratum is a grand measure of inequality in the returns to work that embodies all monetary and nonpecuniary returns."* (Hamermesh, 1999, p. 1086)

[2] They consider the following job characteristics: set own schedule, telecommute, physical demands, fast paced/relaxed work, independence, 10-20 days paid time off, work in team, training opportunities, positive impact on society.

[3] For example, in the *Glassdoor Best Places To Work In 2021* ranking high ranked firms are often associated with *transparent senior leadership* and *mission-driven company culture*, suggesting that rather intangible characteristics are important for workers too (Glassdoor, 2021).

1996 and 2011. Two features of this matched employer-employee data make it attractive for my study. First, it provides daily information on people's employment status, allowing me to follow workers across firms.[4] Second, it provides me with an uncensored measure of earnings, which I can combine with information on whether one is a full-time worker to get a high-quality measure of workers' wage. My main sample focuses on male full-time workers, where I split the sample in two intervals, 1996–2003 and 2004–2011. The 1996–2003 sample covers 800,000 workers at 4,500 employers, and the 2004–2011 sample covers 960,000 workers at 5,900 employers.

I measure voluntary employer-to-employer transitions, which are those that do not follow a layoff, or firm-level dynamics such as firm mergers and takeovers.[5] I then describe patterns of worker flows between employers. For example, I find that employers in the *manufacturing* and *public administration/education* industry attract more workers from other employers than they lose workers. I then show wage differentials associated with employer-to-employer transitions. I find that while employers in *manufacturing* pay a wage premium, this is not the case for employers in *public administration/education*, where many workers even accept a wage decrease.[6] A possible explanation for this is that employers in *public administration/education* are attractive to workers for non-wage reasons.

I develop a structural interpretation of these reduced form patterns through an on-the-job search model in the vein of Burdett and Mortensen (1998). Workers search for job offers, which they receive at Poisson rate. Employers' job offers consist of a wage, and an employer-specific non-wage value. In addition, workers have an idiosyncratic valuation for each employer. When receiving an offer from an outside employer, workers compare it to the offer of their current employer, and transition to the outside employer if it offers them greater value than their current employer. I assume that the value of a job for a worker is an additive combination of the log-wage, the employer-specific non-wage value, and the worker-employer idiosyncratic value.[7]

My model gives rise to a simple probit-style likelihood function, where every likelihood contribution represents a job-to-job transition between two employers.[8] I account for differing employer sizes and the intensity with which employers make job offers to each other's em-

[4] I use the terms firm and employer interchangeably.

[5] I exclude layoffs to the extent they are observed registered by the unemployment agency, and apply the procedure by Sorkin (2018) to account for unobserved layoffs at contracting firms.

[6] This pattern of industry-wage differentials is also found in Krueger and Summers (1988) and Gruetter and Lalive (2009).

[7] The underlying assumption is that workers' valuation for employers' non-wage value is proportional to wage. This is supported by Maestas et al. (2018) finding that workers' willingness to pay for non-wage characteristics is about the same fraction of wage for all quintiles of the wage distribution.

[8] I show that employer-to-employer transitions observed in the data are sufficient for identification, which is necessary because I do not observe when a worker rejects a job offer from an outside employer.

ployees by appropriately weighting each likelihood contribution.[9] I allow for heterogeneity between workers in two ways: First, I let the intensity with which workers receive offers from different employers depend on the worker's current employer.[10] Second, I allow the non-wage value workers are offered by an employer to be heterogeneous through a worker-employer idiosyncratic value component. I estimate three parameters with my model: The first is each employer's non-wage value.[11] The second parameter identifies the importance of wage, relative to non-wage value, for job value. With this parameter, I can convert non-wage value to a log-wage equivalent scale. The third parameter is the variance of the employer-worker idiosyncratic non-wage value.

I estimate the search model separately for the 1996–2003 period and for the 2004–2011 period. I then combine the search model estimates with wage information from my data, which gives me an estimate of the distribution of job value among all workers. I find a positive correlation between wage and non-wage value for both periods, reflecting sorting of workers with high wages to firms offering high non-wage value. Job value inequality is thus considerably greater than wage inequality. In both, 1996–2003 and 2004–2011, 43 percent of job value variance is explained by wage, and 57 percent by non-wage value.[12]

I find that between 1996–2003 and 2004–2011, job value variance increases by 8 percent. Job value variance can increase for three reasons: variance of wage, variance of non-wage, and their covariance. I find that neither the variance of wage nor the variance of non-wage value did increase much. Thus, the main driver of the increase in job value variance is an increase in covariance between wage and non-wage value. To understand the sources of this increase, I decompose wage following Abowd et al. (1999) into a part systematically attributable to worker quality, and a firm wage premium. I find that the increase in job value variance is mainly due to a striking change in the covariance between firm wage premium and firm non-wage value. While in 1996–2003 the covariance between firm wage premium and firm non-wage value is negative, it is positive in 2004–2011.[13]

Economically, the covariance between firm wage premium and firm non-wage value mea-

[9] While I directly observe employer size in the data, I follow Bonhomme and Jolivet (2009) and Sorkin (2018) and estimate the intensity with which employers make offers from the number of workers they hire from non-employment. I show that my results do not change when the offer distribution is estimated under alternative assumptions.

[10] With this, I allow for sorting of workers across employers.

[11] I actually estimate 4,500 (1996–2003) and 5,900 (2004–2011) parameters here, one for each employer in my sample.

[12] This is close to Taber and Vejlin (2020) finding that 49 percent of job value variance is explained by wage, and 51 percent by non-wage value.

[13] The correlation between firm non-wage value and the firm wage premium in 1996–2003 is close to the correlation Hall and Mueller (2018) find between the non-wage value and the wage of jobs offered to unemployed job seekers.

sures the importance of compensating differentials relative to firm-level rents (Robinson, 1933; Rosen, 1986). Intuitively, if firms fully compensate through wage for the quality of their non-wage characteristics, firm wage and non-wage value will be perfectly negatively correlated. If there are no compensating differentials, and dispersion of wage and non-wage value is purely due to firms offering rents, firm wage and non-wage value will be perfectly positively correlated. My results show that compensating differentials were attenuating job value inequality 1996–2003. By 2004–2011, however, they have disappeared and dispersion of firm-level rents has increased, leading to an increase in job value inequality.

What fundamental developments can explain these patterns? I interpret the findings in the framework of a simple monopsonistic competition model (Manning, 2013). In this framework, firms first decide which total value they offer to workers, and second, how to best divide it into wage and non-wage value (Lang and Majumdar, 2004). Thus, I can separately address the question of why rent dispersion increased, and why compensating differentials disappeared. I test multiple potential explanations for the increase in rent dispersion from 1996–2003 to 2004–2011. I find that a decline in the elasticity of labor supply, caused by an increase in the idiosyncrasy of workers' preferences over employers, explains part of the increase in rent dispersion among firms (Card et al., 2018; Lamadon et al., 2021). I then provide evidence that an immigration-induced increase in labor supply for firms offering low value also accounts for part of the increase in rent dispersion (Borjas, 2014).

I show that the disappearing of compensating differentials must be explained by firm-specific (or industry-specific) changes in marginal cost of non-wage value provision (Rosen, 1986).[14] I derive an estimate of firms' marginal cost of non-wage value provision in 1996–2003 and 2004–2011. I do so by combining my estimates of firms' non-wage value and firms' wage premium with the assumption that firms equalize marginal cost of providing job value through wage and non-wage value. I find that the cost of non-wage value provision declined most in the construction and the real estate service industry, where firms tend to compensate workers for low non-wage value with a wage premium.

I conclude the paper by discussing the robustness of my results. My model of the labor market allows for tractable identification of non-wage values. The flip side is that it is quite stylized and omits some mechanisms discussed in the literature, including systematic forms of preference heterogeneity, labor market learning, or firm-specific human capital. I provide evidence that these mechanisms are unlikely to have an important effect on my results. Another potential limitation of my framework is related to a data requirement of my estimator: For employers'

[14]This solely relies on the assumption that employers are cost minimizing when deciding how to divide the value they offer to workers between wage and non-wage value, which is plausible even for public sector employers, and with union bargaining.

non-wage value in my model to be identified, a sufficient number of workers moving from and to an employer is required. Small employers often do not satisfy this requirement, meaning that I cannot identify their non-wage value. I show evidence that my sample nevertheless reflects well the overall structure and dynamics of the labor market.

This paper contributes to the literature estimating job values in search environments (Bonhomme and Jolivet, 2009; Becker, 2011; Sullivan and To, 2014; Hall and Mueller, 2018; Sorkin, 2018; Taber and Vejlin, 2020; Jarosch, 2021). Most closely related are Sorkin (2018) and Taber and Vejlin (2020), who also rely on worker flows between firms to identify total job values. Relative to Sorkin, I incorporate wage differentials in the estimation of my model, which allows me to separately identify the contribution of wage and non-wage value to job value.[15] Taber and Vejlin (2020) also separate job value into a wage and a non-wage value part. They rely on a rich structural model in which parameters are only indirectly identified by the data.[16] In contrast, my model directly uses patterns observed in the data and provides a transparent estimation framework. Taber and Vejlin (2020) find that non-wage value accounts for half of workers' flow utility, but do not provide any evidence on how non-wage value varies along the wage distribution.

This paper also contributes to the literature attempting to explain wage inequalities with compensating differentials. Krueger and Summers (1988) find that differences in non-wage characteristics of jobs cannot explain inter-industry wage differentials.[17] Subsequent work has shown that search frictions (Hwang et al., 1998; Bonhomme and Jolivet, 2009) as well as idiosyncratic preferences of workers over firms (Lamadon et al., 2021; Manning, 2021) can explain this result.[18] My model incorporates both, search frictions and idiosyncratic preferences of workers over firms. I add to the literature by showing in a simple model of monopsonistic competition how they can both lead to rent dispersion among firms nullifying the inequality attenuating effect of compensating differentials.

The rest of the paper is organized as follows. The next section describes the data and provides descriptive evidence on patterns of employer-to-employer transition. Section 3 discusses identification of non-wage values. Section 4 presents the results. Robustness is considered in Section 5, and Section 6 concludes.

[15] The job value identified by Sorkin are in utility units with an unknown scale and thus cannot be separated into wage and non-wage value.

[16] The richness of the model by Taber and Vejlin (2020) is driven by their attempt to decompose total labor market wage and utility variation into variation due to pre-market skills variation, learning by doing, preferences for non-pecuniary aspects, monopsony, and search frictions.

[17] Similarly, Katz et al. (1989) find a slight positive correlation between the industry wage premium and the quality of non-wage characteristics.

[18] An earlier literature emphasizes the role of unobserved worker heterogeneity (Hwang et al., 1992; Brown, 1980), which is of second order in studies relying on panel data and within-individual variation.

2 Background, Data and Descriptive Evidence

Background The Austrian labor market combines broad institutional regulation with high flexibility. Virtually all jobs are covered by collective bargaining agreements setting wage floors and minimum non-wage work arrangements (Glassner and Hofmann, 2019).[19] For most jobs, however, provisions from collective bargaining agreements are not binding. For example, Leoni et al. (2011) find that actual wages in manufacturing in the early 2000s were on average 20-30% higher than collective bargaining wage floors. The Austrian labor market thus maintains a high degree of flexibility. Job creation and job destruction rates in most industries are comparable to those in the US (Stiglbauer et al., 2003). Between 1996 and 2011, the Austrian labor market was characterized by steady conditions. Unemployment was among the lowest in Europe, ranging from 3.5 percent in 2000 to 6.5 percent after the great recession in 2009. The wage structure was stable between 1996 and 2011 (Figure A.1).

Data I use data from two administrative sources, which together allow me to follow workers across firms and observe their wages. The Austrian social security data (Zweimüller et al., 2009) provide matched employer-employee data on the universe of Austrian private sector dependent employment and public sector employment under private labor law.[20] The social security data contain detailed daily information on worker labor market status (e.g., employed, unemployed, retired). Each employment spell is linked to an employer identifier and information on the employer's industry and location.[21]

The second data source is the Austrian wage tax data (Büchi, 2008). They cover the universe of private and public sector dependent employment. The wage tax data are based on wage tax forms annually submitted by employers. They contain workers' uncensored gross labor earnings,[22] and since the year 2002 an indicator whether an individual is working full-time or part-time. Before 2002, over 97% of working men were full-time employed (Figure A.2). When limiting attention to men and excluding part-time workers after 2002, gross earnings from wage tax data therefore represent a high-quality measure of wage, as large variation in working hours is ruled out.[23]

[19]Non-wage characteristics are, for example, dismissal protection or continued remuneration in case of sickness (Glassner and Hofmann, 2019).

[20]In 2004 34 percent of public sector employees were employed with private sector contracts and therewith part of the social security data (Bundeskanzleramt, 2021).

[21]Most establishments of multi-establishment employers in Austria have a common employer-identifier in the social security data (Fink et al., 2010).

[22]Including bonus payments.

[23]Table A.1 shows the distribution of full-time workers' weekly hours across industries based on the *Mikrozensus* survey. Industry-level averages of weekly working hours range from 39.8 hours in utilities to 44.4 hours in hotel and restaurant.

Matched Employer-Employee Panel I construct two consecutive yearly panels of the Austrian workforce, from 1996 to 2003 and from 2004 to 2011, by combining employment information from the social security data with wage information from the wage tax data.[24] Individuals in my panel satisfy the following three conditions: (1) The person is male and not a part-time worker, (2) he is working for the entire calendar year, and (3) holds only one single job. Condition (1) allows me to interpret earnings as wages. Condition (2) and (3) ensure that I can link a person-year observation in the social security data to the wage tax data. Apart from being required by the data, these conditions are also motivated by my framework. I interpret employer-to-employer transitions as the result of a worker's binary choice over two jobs. This is only suitable for workers holding one single job at a time. The condition that workers must work for the same employer for at least one entire calendar year excludes workers in seasonal employment, where the termination of an employment spell in most cases is caused by the end of the employer's business season, rather than following a worker's choice.

The model I will introduce in Section 3 is only identified for employers strongly connected by employer-to-employer transitions.[25] The restriction concerns the network of worker flows between employers. An employer is in a strongly connected set if it hires at least one worker from another employer in this strongly connected set, and has at least one of its workers hired by another employer in this strongly connected set.[26] To ensure my model is well-identified, I only consider employers that have overall at least five employer-to-employer transitions with other employers in the strongly connected set.[27]

[24]To the best of my knowledge, this is the first study on Austria to rely on wage information from Austrian wage tax data, while all previous studies on Austria have estimated earnings from the social security data (e.g., Card et al., 2007; Lalive and Zweimüller, 2009; Nekoei and Weber, 2017).

[25]Technically, the strongly contentedness condition follows from the maximum likelihood estimator regularity condition that the identified parameter vector needs to be an interior point (see Sections 3.3 and Appendix E.2).

[26]In my sample I consider the largest strongly connected set, that is, the set containing most employers.

[27]This restriction is motivated by the so-called *incidental parameter bias* (Greene, 2015, 188–192), which is relevant for my model because I identify a large number of fixed effects in a non-linear model (cf. Section 3.3). I implement this restriction in a loop, where I sequentially drop firms with fewer than 5 employer-to-employer transitions with the strongly connected set, until every firm has at lest 5 employer-to-employer transitions with the strongly connected set. The resulting strongly connected set contains more than 10 times as many observations (transitions) than subjects (firm) in both periods, 1996–2003 and 2004–2011. It has been shown for the panel fixed effects probit estimator (which is similar to my estimator) that incidental parameter bias is small when there are at least 10 observations per subject (Hahn and Newey, 2004, Table 3 and 4, pp. 1306–1307; Greene, 2002, Table 2, p. 16; Heckman, 1981, Table 4.1, p. 191).

Table 1: POPULATION AND STRONGLY CONNECTED SAMPLE 1996–2003 & 2004–2011

	1996 – 2003		2004–2011	
	All	Strongly connected	All	Strongly connected
	(1)	(2)	(3)	(4)
A. Sample size				
People-years	9,526,421	4,513,833	9,906,446	5,480,901
People	1,621,545	797,492	1,712,585	964,635
Employers	193,633	4,544	182,811	5,944
B. Summary Statistics				
Mean age	38.80	39.07	40.21	40.21
Share blue collar	0.48	0.43	0.43	0.39
Median monthly wage (2012 €)	3,048	3,345	3,196	3,481
Mean log monthly wage	8.09	8.19	8.14	8.23
Mean log monthly wage	8.09	8.19	8.14	8.23
Var log monthly wage	0.21	0.20	0.21	0.20
C. Industry Shares				
Manufacturing	0.31	0.39	0.31	0.39
Utilities	0.02	0.03	0.02	0.03
Construction	0.10	0.05	0.10	0.06
Retail trade, cars	0.16	0.10	0.15	0.10
Transportation	0.07	0.07	0.07	0.08
Hotel and restaurant	0.02	0.00	0.02	0.00
Information and communication	0.02	0.02	0.03	0.03
Finance and insurance	0.06	0.08	0.05	0.06
Real estate	0.02	0.02	0.02	0.02
Prof./scientific/tech. services	0.05	0.05	0.04	0.03
Services	0.04	0.04	0.05	0.05
Public admin./education	0.10	0.13	0.10	0.13
Health and social	0.02	0.02	0.02	0.02
D. Employer-to-employer transitions				
Transitions	159,199	58,349	178,835	74,271
Share excess separations	0.49	0.54	0.48	0.47
Mean log wage increase	0.11	0.11	0.09	0.10
Mean log wage increase (adjusted)†	0.05	0.06	0.05	0.05
Share wage increase (adj.)	0.58	0.60	0.59	0.60
Share both employers same industry	0.44	0.47	0.43	0.45

Notes: This table reports summary statistics on all male full time workers (columns 1 and 3) and those in the sample of strongly connected firms (columns 2 and 4). The industry classification is based on NACE Rev. 2 main sections. I combine section D & E (Utilities), O & P (Public admin./education) and N & S (Services). The following industries are not shown: Agriculture, forestry and fishing, Mining, Arts and entertainment, Households as employers, (All share people-years in 1996–2003 <0.01). All summary statistics on transitions (Panel D. after *Share excess separations*) are with observations weighted by their probability of being an excess separation as defined in the text.

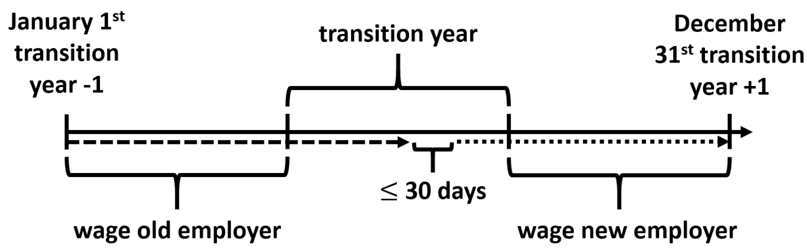
† The wage at the old employer is observed in year t, and the wage at the new employer in year $t+2$. I substract time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2)

Table 1 shows descriptive statistics on the 1996 to 2003 and the 2004 to 2011 employment panel. Columns 1 and 3 show statistics on all employers, while columns 2 and 4 consider the sample of strongly connected employers. Panel A. shows that while there are much fewer employers in the strongly connected sample, columns 2 and 4 still cover more than half of the labor market when measured through the number of people-year observations. This reflects that the strongly connectedness condition is much more likely to be satisfied by medium-sized and large employers. Panel B. shows that while workers in my sample earn higher wages on average, wage dispersion is about the same in my sample as in the Austrian labor market overall.

Concerns related to external validity may also arise because my sample restricts attention to male workers and to full-time workers. In Appendix D I show that my sample of strongly connected employers well reflects the overall structure of the Austrian labor market, and that dynamics are very similar among workers not considered in my sample. I thus conclude that my results are likely to hold for the Austrian labor market overall.

Employer-to-Employer Transitions Figure 1 shows how I identify employer-to-employer transitions. First, a change of employer is classified as an employer-to-employer transition if there are at most 30 days of non-employment between two consecutive employment spells. Second, the worker must have been working for the old employer since the start of the calendar year preceding the transition, and he must work for the new employer until the end of the calendar year succeeding the transition.[28]

Figure 1: EMPLOYER-TO-EMPLOYER TRANSITIONS



Notes: This figure illustrates how I identify employer-to-employer transitions and associated wage differentials. A transition in year t is considered an employer-to-employer transition if the following criteria are satisfied: (1) Less than 30 days between two employment spells, and no unemployment spell in between. (2) The worker works the full calendar year before the year of the transition for the old employer. (3) The worker works the full calendar year after the year of the transition for the new employer.

My model is built around the idea that employer-to-employer transitions are the outcome

[28]The year of the transition is the year of the last day of employment at the old employer.

of a worker's choice between a job offer from his old employer and a job offer from his new employer. I therefore exclude all transitions that most likely are not the result of such worker decisions. Specifically, I exclude all transitions that follow a layoff recorded in the social security data.[29] I also exclude all transitions that follow firm-level dynamics such as firm renaming, takeovers, mergers, spin-offs, or firm closures, which I identify following Fink et al. (2010).[30]

Even after removing these transitions, there are involuntary employer-to-employer transitions left in my sample. In particular, my data do not allow me to identify cases where a worker is laid off and finds a new job without an interrupting unemployment spell. Sorkin (2018) proposes a probabilistic approach to correct for these transitions. The underlying idea is that these transitions are most likely to happen at contracting firms. To see this approach consider Figure 2, which shows employer-to-employer and employer-to-nonemployment separation probabilities as a function of the annual employer growth. I calculate the average employer-to-employer separation rate at expanding employers, which I use as an estimate for the expected separation rate from voluntary employer-to-employer transitions. When an employer is contracting and the separation rate is in excess of the expected rate, I consider these separations as exogenous due to an employer-level shock. I calculate the expected rates by industry, and then downweight separations at contracting employers with $(1 - \frac{\text{excess}}{\text{excess+expected}})$.[31]

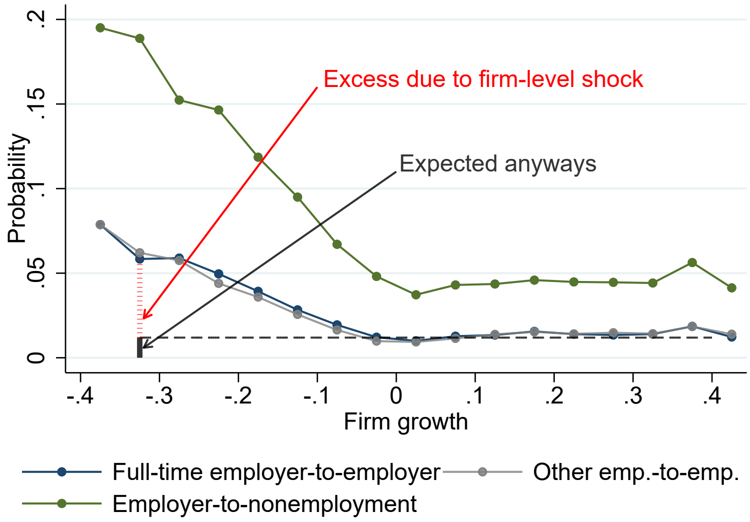
Panel D. of Table 1 shows descriptive statistics on employer-to-employer transitions. 58,349 transitions occur between firms in my sample for 1996–2003 and 74,271 transitions between 2004–2011. In both periods, employer-to-employer transitions come on average with a log wage increase of about 0.05, and wage increases for around 60 percent of transitions. Table A.2 shows in detail how I obtain the transitions in Table 1 from all employment spells that end in the two sample periods.

[29] Laid-off workers are eligible for unemployment benefits from the first day of unemployment. Workers who quit face a waiting period of 4 weeks. This implies that I can identify laid-off workers from the social security data to the extent that the lay-off leads to receiving unemployment benefit.

[30] I identify employer-level dynamics from collective actions of groups of workers, as recorded in the social security data. For example, an employer takeover is identified if an employer-identifier disappears from the records and if at least two thirds of workers work for the same employer in the following quarter. See Appendix B for details.

[31] Annual separation rates at expanding firms are highest in Services (3 percent) and lowest in Public administration/education and Utilites (1 percent). See Table A.3 for separation rates by industry.

Figure 2: EMPLOYMENT GROWTH AND TRANSITION PROBABILITIES



Notes: This figure shows the probability (per year) a worker in column 3 of Table 1 makes a transition, by 0.05 employer growth rate bin. *Full-time employer-to-employer* corresponds to the employer-to-employer transitions defined in this section. *Other employer-to-employer* corresponds to all transitions in which the worker starts at the new employer within 30 days, but do otherwise not satisfy the conditions detailed in this section. *Employer-to-nonemployment* corresponds to employment spells ending in year $t+1$ for which the worker does not join a new employer within 30 days. Share excess transitions $\frac{\text{excess}}{\text{excess+expected}}$. Figure A.6 shows the corresponding figure for the 1996–2003 sample.

Descriptive Evidence on Transitions, Wage Differentials, and Non-Wage Values I will now discuss descriptive evidence on employer-to-employer transitions and wage differentials between firms, and illustrate how we can use them to learn about firms' non-wage values. I will use evidence aggregated on the industry-level for the 2004–2011 panel. The same reasoning applies for 1996–2003, and the corresponding industry-level descriptive statistics are shown in Appendix C.

Figure 3 a shows how workers transition between industries. Each cell measures the intensity of employer-to-employer transitions from an industry in the corresponding row to an industry in the corresponding column. The intensity measures how many employer-to-employer transitions actually happen from a row-industry to a column-industry, relative to how many would be expected to happen if mobility was random with respect to industries.[32] Thus the greater the value of a cell the more intensively workers transition from the corresponding row-industry to the corresponding column-industry. Values above 1 represent intensities above the

[32]Each cell corresponding to row-industry j and column-industry k equals $\frac{\text{transitions}_{jk}}{\sum_{s\in J}\sum_{l\in J}\text{transitions}_{sl}} * \left(\frac{\sum_{l\in J}\text{transitions}_{jl}}{\sum_{s\in J}\sum_{l\in J}\text{transitions}_{sl}} * \frac{\sum_{s\in J}\text{transitions}_{sk}}{\sum_{s\in J}\sum_{l\in J}\text{transitions}_{sl}}\right)^{-1}$, where transitions_{jk} denotes the number of employer-to-employer transitions between industry j and industry k, and J the set of all industries.

random mobility counterfactual, and values below 1 intensities below. The large variation in intensities depicted in Figure 3 a shows that mobility between industries is clearly non-random. Unsurprisingly, the intensities are largest along the diagonal, reflecting that most employer-to-employer transitions happen within the same industry. There are also systematic patterns between some industries, for example between *public administration/education* and *health and social services*, reflected by high intensities in the top-right corner cells in Figure 3 a.

Table A.4 summarizes, by industry, the number of workers employers attract from other employers, and compares it to the number of workers they loose to other employers. Two industries, *manufacturing* and *public administration/education*, stand out because they attract around 20 percent more workers from other employers than they lose to other employers. This suggests that working in *manufacturing* and *public administration/education* is relatively attractive for workers, that is, they are willing to give up their old job to join an employer in these two industries, but not as willing to give up their job in these two industries to work elsewhere.[33]

Figure 3 b provides evidence on the extent to which *manufacturing* and *public administration/education* employers' attractiveness can be explained by wage premia. It shows the average wage increase that comes with a transition from an employer in the row-industry to an employer in the column-industry. We see rather dark colors in the column *manufacturing*, reflecting that workers who join *manufacturing* typically see their wage increase. On average, workers who join *manufacturing* see their wage increase by 6.9 percent.[34] In contrast, workers who leave manufacturing on average see their wage increase by only 0.5 percent, reflected by rather bright colors in the *manufacturing* row. The exact opposite picture arises for *public administration/education*. Workers who join *public administration/education* on average see their wage decline by 2 percent, while workers who leave it see their wage increase by 8.3 percent on average.

Overall, industry-level descriptive statistics suggest that while employers in *manufacturing* and *public administration/education* are attractive for workers, it is only in the case of manufacturing that this can at least in part be explained by manufacturing employers paying a wage premia. In *public administration/education*, however, there must be something other than the wage making it attractive for workers. This is exactly the intuition behind the identification of non-wage values in my model, which I will explain in the following section.

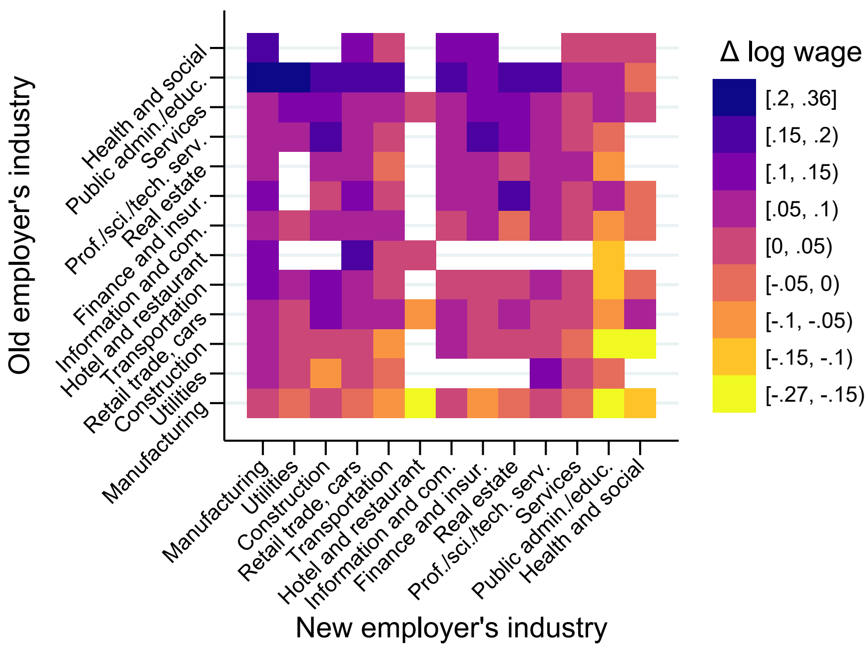
[33]On the other hand, employers in *construction*, *real estate*, and *services* lose more workers to other employers than they hire from them. This suggests that employers in these industries are rather unattractive for workers. The *services* industry includes mostly industries providing low-skilled services (NACE Rev. 2 codes N & S).

[34]Table A.5 shows average wage differentials for employer-to-employer transitions by industry.

Figure 3: Employer-to-Employer Transitions and Wage Differentials

(a) Intensity of Employer-to-Employer Transitions

(b) Wage Differentials



Notes: Figure a shows the intensity of employer-to-employer transitions between industries 2004–2011. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from the row-industry to the column-industry than expected under random mobility. See text for a formal definition of the intensity. Figure b shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions with the old employer in the row-industry in the new employer in the column-industry. Missing cells in figure b contain fewer than 10 observations. Both figures are based on transitions between employers in the strongly connected 2004–2011 sample (column 4 in Table 1). See Figure A.7 for transitions in the 1996–2003 sample, and Figure A.10 for employer-to-employer transitions of all workers in 2004–2011.

3 Identification of Non-Wage Values

In the following, I construct an on-the-job search model in the vein of Burdett and Mortensen (1998). The model is partial equilibrium, meaning that I take firm behavior as exogenously given. Employers post contracts that workers either accept or not, so there is no bargaining. The model incorporates search frictions in the form of a stochastic rate at which workers receive job offers. In the framework of this model, I interpret voluntary employer-to-employer transition as the result of a binary choice over two job offers, one from the employer that the worker joins and one from the employer that the worker leaves. This then allows me to identify employers' non-wage values from the extent to which worker choice can or cannot be explained by wage differentials. I focus on a discussion of the model's structure and intuition in this section. Additional information on the model, including workers' value functions, can be found in Appendix E.

3.1 Primitives

Employers Each employer $j \in J$ is fully characterized by the tuple $\langle \psi_j, a_j, g_j, \boldsymbol{f_j} \rangle$. ψ_j denotes the log-wage premium, which I assume following Abowd et al. (1999) (henceforth AKM) that the employer pays to every worker equally. a_j denotes the non-wage value employer j offers to all its workers equally.[35] g_j denotes the size of the employer, that is, the number of employees of employer j. $\boldsymbol{f_j} = [f_{j1}, ..., f_{j,k \neq j}, f_{j,J}]$ denotes the vector of employer j's offer intensities, that is, the intensity with which employer j makes employment offers to workers at all other employers.

Workers Employed workers are characterized by the pair $\langle \alpha_{it}, j \rangle$. α_{it} denotes, following AKM, worker i's skills, labor market experience, and other factors for which the worker is compensated equally by all employers. j denotes worker i's current employer. I assume a worker's value from working at employer j is a linear combination of his log wage w_{ij}, the log of his current employer's non-wage value a_j, and the worker's idiosyncratic valuation for working at employer j ϵ_{ij}:[36]

$$V_{ij} = \gamma ln(w_{ij}) + ln(a_j) + \epsilon_{ij} \tag{1}$$

[35] One can think of $a_j = a(\mathbf{m}_j)$, where $\mathbf{m}_j$ is an arbitrary-dimensional vector containing characteristics that are valuable to a worker when working at employer j, which are converted to a non-wage value through the function $a()$.

[36] Throughout the paper the term "utility" refers to job value, that is, the value of the value function, and *not* the flow utility.

This log-additive form is supported by Maestas et al. (2018, Figure 7) and Mas and Pallais (2017, p. 3754) finding that individuals with high vs. low wage are willing to give up about the same fraction of wage for various amenities. I normalize $\gamma = 1$, which implies that V_{ij}, $ln(a)$ and ϵ_{it} are in log-wage equivalent units.[37]

3.2 Search, Offers and Employer-to-Employer Transitions

Employed workers search for job offers from other employers, which they receive at an exogenous rate. A job offer consists of a pair $\langle ln(w_{ij}), a_j \rangle$, with $ln(w_{ij}) = \alpha_{it} + \tilde{\psi}_j + \eta_{ij}$. η_{ij} is a random draw from a symmetric and non-degenerate mean-zero distribution. $\tilde{\psi}_j = \psi_j - \mathbb{E}[\eta_{ij}|\text{offer accepted}]$ is the pay premium employer j offers, where employers adjust for the fact that offers with a higher η_{ij} are more likely to be accepted. So by offering $\tilde{\psi}_j$, employer j ensures the actual average log-wage premium he pays to its workers equals ψ_j.

When a worker employed at employer j receives a job offer from an outside employer k, he draws a new job offer from his current employer j and makes a binary choice over the two offers:

$$\begin{aligned} P(V_{ik} > V_{ij}) &= P(ln(w_{ik}) + ln(a_k) + \epsilon_{ik} > ln(w_{ij}) + ln(a_j) + \epsilon_{ij}) \\ &= \Phi(ln(w_{ik}) - ln(w_{ij}) + ln(a_k) - ln(a_j)) \end{aligned} \tag{2}$$

where Φ denotes the cumulative distribution function of a normal distribution with mean zero and variance $2\sigma^2$ and the last equality follows from assuming that $\epsilon_{is} \sim i.i.d.\ \mathrm{N}(0, \sigma^2)$, so $(\epsilon_{ij} - \epsilon_{ik}) \sim i.i.d.\ \mathrm{N}(0, 2\sigma^2)$.

With an ideal dataset in which the analyst observes all offers from outside employers and all binary choices of employed workers, the structure put on the environment so far would be sufficient to estimate the $ln(a_j)$ of each employer and σ by simply maximizing the joint-likelihood of all binary choices. With the administrative data I have available, however, I only observe job offers that employed workers accept, which are the employer-to-employer transitions discussed in the previous section. In particular, I do not observe when workers receive a job offer from an outside employer and choose to stay with the current employer. Hence, in order to render this model estimable with my data, I need some measure of the number of offers employers make to employees of other employers. I follow Bonhomme and Jolivet (2009) and Sorkin (2018) in assuming that non-employed workers search from the same offer distribution as employed workers, and that non-employed workers do not reject job offers. Therefore, I can recover the intensity with which employers make job offers from the number

[37] γ converts log-wage to job value units. By setting $\gamma = 1$, I set the scale of job value to equal the log-wage scale.

of non-employed workers they hire. In addition, I assume the following for the pattern with which employers make offers to each others' workers:

> Assumption 1: $\frac{f_{jk}}{f_j^{NE}} = \frac{f_{kj}}{f_k^{NE}}$; There exists some measure of the intensity with which employers make offers f^{NE}, and the probability a worker at employer k receives an offer from employer j, relative to the total number of offers made by employer j, equals the probability a worker at employer j receives an offer from employer k, relative to the total number of offers made by employer k.

Intuitively, this assumption states that if an employer makes offers to another employer's workers with a higher intensity than vice versa, then it must also be that this employer makes offers with an overall higher intensity. While this assumption is in line with random search, that is, that all workers receive job offers from a particular employer with equal probability, it is less restrictive in that it allows for directed search, that is, that the probability of receiving a job offer from a particular employer depends on a worker's current employer. For example, in my model f_{jk} is allowed to be higher if employers k and j rely on the same type of labor input (with respect to education, skills, experience), which is intuitively as well as empirically plausible (see, for example, Nimczik, 2020).

This model provides enough structure to identify employers' non-wage values from observed employer-to-employer transitions. In the following, I discuss how I estimate the model.

Proposition 1. Let $\Omega = ([j, k, \Delta ln(w)]_1, ..., [j, k, \Delta ln(w)]_S)$ be the set of all S employer-to-employer transitions between all employers in J generated under the model above. The joint likelihood of all S transitions is:

$$\mathcal{L} = \prod_{s=1}^{S} \Phi[(ln(w_{(i,t),j}) - ln(w_{(i,t),k})) + ln(a_j) - ln(a_k)]^{\frac{1}{f_j^{NE}}\frac{1}{g_k}}$$

Proof. See Appendix E.2. □

This proposition states that the likelihood the above model results in the set S of employer-to-employer transitions is simply the product of the likelihood contributions of the transitions, each of them appropriately weighted. To see the intuition behind Proposition 1, it is instructive to consider the case when all employers make equally many offers, so f_j^{NE} is constant, and all employers are of equal size, so g_j is constant. In this case, Proposition 1 states that the likelihood of observing the S transitions is simply the product of the likelihood contributions of these S transitions. This holds true because for every pair of employers j and k the number of workers at employer j that receives an employment offer from employer k, but rejects the offer, is equivalent to the number of workers at employer k that receives an employment offer from employer j and accepts, and vice versa.

Starting from this, we can see the intuition for the likelihood-weight $\frac{1}{f_j^{NE}}$, which is the inverse of the offer intensity of the employer the worker *joins*. Suppose employers j and k are otherwise exactly the same, but that employer j makes twice as many job offers as employer k. Consequently, we will observe twice as many employer-to-employer transitions from employer k to employer j as from employer j to employer k. This is, however, not because employer k offers any better non-wage value than employer j, but only because it recruits more intensively. By downweighting the likelihood contribution of every employer-to-employer transition from employer k to employer j by one half, the estimator accounts for the difference in offer intensity between these employers.

A very similar intuition applies for the likelihood weight $\frac{1}{g_k}$, which is the inverse of the number of employees at the employer the worker *leaves*. Consider two employers that are exactly the same, except that one has twice as many employees as the other. In this case, we will observe twice as many employees leaving the larger employer than the smaller. By downweighting the likelihood contribution of every employer-to-employer transition away from the larger employer by one half, the estimator accounts for the difference in size between these employers.

Due to the simple form of the likelihood function in Proposition 1, it is relatively easy to pin down the variation identifying employer non-wage value. First, employer non-wage value is driven by the net flow of workers (after accounting for employer size and offer intensity) between employers, where employer j's non-wage value is higher relative to employer k's non-wage value if there is more worker flow from employer k to employer j. This is the same source of variation that Sorkin (2018) exploits. The novelty of my model is that I use wage differentials between employers for identification, where, assuming constant worker flows, employer j's non-wage value is higher relative to employer k's non-wage value if wages are *lower* at employer j relative to employer k.[38] Another novelty of my model is that I allow the probability with which a worker receives a job offer from a particular employer to depend on the worker's current employer.[39] This implies that my model generates sorting of workers to employers without modeling comparative advantages or systematic preferences of workers

[38]Because there is random variation in firms' wage offer through η, which affects workers' probability of accepting a job offer, I can separately identify firm non-wage value and firm wage, even though the only systematic variation of non-wage value and wage (net of the person-specific component) is on the firm-level (see Appendix E.2).

[39]I allow this probability to vary for non-employed workers as well.

over employers, thus allowing for high tractability.[40]

3.3 Estimation

I estimate the model separately using the 1996–2003 panel and the 2004–2011 panel. For strongly connected employers, the likelihood function in Proposition 1 is continuous and twice differentiable. This implies that I can use standard maximum likelihood routines in estimation.[41]

Search Model Estimates Table 2 shows the distribution of the two model parameters I use in estimation, for the 1996–2003 and the 2004–2011 panels. I measure the employer size parameter g by the number of people-years per employer. The hires from non-employment correspond to the total number of individuals hired that were non-employed for at least 30 days. Both measures are totals over 8 years.[42]

Employers' non-wage values $ln(a)$ in Proposition 1 are identified relative to a base employer's non-wage value, which I select to be the employer with the most employer-to-employer transitions. Table 2 summarizes the estimates of employers' non-wage values. As each employer's non-wage value is only identified relative to a base employer, I standardize the distribution of employers' non-wage values to have mean zero. To avoid having the dispersion of employers' non-wage values driven by sampling variation, I shrink the estimates of employers' non-wage values towards the respective industry by federal state average using an empirical bayes approach (see Appendix F for details). Table 2 shows that while this reduces variation, in particular in the tails of the distribution, the shrinked non-wage values remain highly correlated with the non-shrinked values. I rely on shrinked non-wage values throughout the paper. Overall, Table 2 does not point to any substantial difference in parameter values and estimates between the 1996–2003 and the 2004–2011 panel.

[40] Sorting through comparative advantages is typically obtained by modeling production complementarities between worker and employer types (Rogerson et al., 2005; Wright et al., 2019). Another approach is to model persistent preferences of workers over employers, locations and industries (Lamadon et al., 2021).

[41] I use Stata's *ml* command and Newton-Raphson. I account for the probability a transition in my sample does not represent a worker-initiated employer-to-employer transition (see Section 2) by weighting every likelihood contribution in Proposition 1 by $(1 - \rho_{kt})$, where ρ_{kt} represents the share of employer-to-employer transitions at employer k in year t that are in excess of the expected number of employer-to-employer transitions.

[42] By the definition of employer-to-employer transitions as detailed in Section 2, for the 2004–2011 panel only person-year observations from 2003 to 2010 are at risk of being hired by another employer because they need to work one full calendar year for the new employer after they are hired. Hence, the appropriate sample period for the calculation of g_j is 2003 to 2010. With regard to the hires made by some employer j, only full-time workers hired from other employers in the years 2004 to 2011 can enter my sample as employer-to-employer transition. Therefore, the appropriate time period to calculate the measure of employer offer intensity on the market for full-time full year workers, f_j, is 2004 to 2011. The same reasoning applies for the 1996–2003 panel.

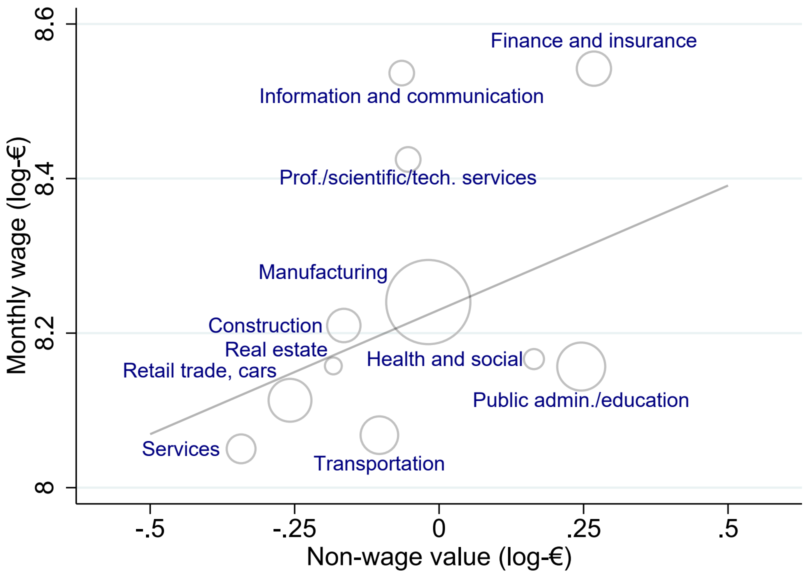
Table 2: SEARCH MODEL ESTIMATES

	Mean	Var	Min	Max
	1996 – 2003			
Parameters				
Firm size (people-years)	799	2136^2	2	56744
Hires from non-employment	60	134^2	1	4918
Estimates				
Firm non-wage value (log €)	0	.36	-3.44	2.38
Shrinked firm non-wage value (log €)	0	.20	-3.04	1.67
Corr(Firm non-wage, Shrinked firm non-wage)	.94			
Number of transitions	58,349			
	2004 – 2011			
Parameters				
Firm size (people-years)	727	1830^2	5	53569
Hires from non-employment	59	132^2	1	4140
Estimates				
Firm non-wage value (log €)	0	.39	-3.45	3.44
Shrinked firm non-wage value (log €)	0	.21	-2.32	1.93
Corr(Firm non-wage, Shrinked firm non-wage)	.94			
Number of transitions	74,271			

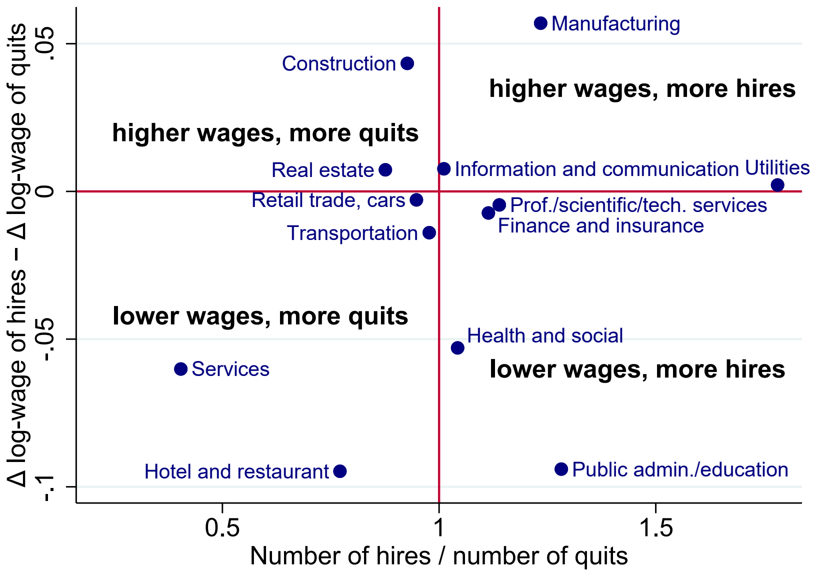
Notes: The panel *Search Model* shows the model parameters and estimates from estimating the model in Proposition 1 on the sample in Table 1, columns 2 and 4. Firm size is measured from 1995 to 2002 (2003 to 2010). Hires from non-employment are measured from 1996 to 2003 (2004 to 2011). Firms' non-wage values are only identified relative to each other and thus standardized to have mean zero. The mean and variance of firm non-wage value and shrinked firm non-wage value are with firms weighted by the number of person-year observations they represent. Shrinkage uses an empirical bayes with industry by federal state averages as prior distribution (see Appendix F for details). I rely on shrinked non-wage values throughout the paper.

Figure 4: Hires, Quits, Wage Differentials and Non-Wage Values

(a) Non-Wage Values



(b) Employer-to-Employer Transitions and Wages



Notes: Figure a shows non-wage values and log-wages by industry, with circle size relative to the number of person-year observations in the corresponding industry. The gray line plots the regression line run at the industry level, with industries weighted by their number of person-year observations. Two industries are not shown in figure a: Utilities (coordinates: (.85,8.47)) and Hotel and restaurant (-.55,7.79). Figure b shows, on the x-axis, the number of employer-to-employer hires divided by the number of employer-to-employer quits (based on columns 3 and 4 of Table A.4), and on the y-axis: Log-wage increase of employer-to-employer hires minus log-wage increase of employer-to-employer quits (corrected for time/experience effects, based on Table A.5). Figures are based on the 2004–2011 sample (column 4 in Table 1). See Figure A.8 for the 1996–2003 sample.

Figure 4 shows, for the 2004–2011 panel, that my estimates of employers' non-wage values

(Figure 4 a) intuitively map to summary statistics on hires and quits (Figure 4 b).[43] For example, we see in Figure 4 a that employers in *public administration/education* offer high non-wage value. Figure 4 b shows that employers in *public administration/education* hire more workers than they loose (x-axis), despite paying lower wages (y-axis). An example of a low non-wage value industry is *construction*, where we see in Figure 4 b that its employers loose more workers than they hire, despite paying higher wages.

Estimation of Wage Components Under my search model, wages assume the following AKM form:

$$ln(w_{it}) = \alpha_i + \psi_{\boldsymbol{J}(i,t)} + \boldsymbol{X}'_{it}\beta + r_{it} \tag{3}$$

where α_i is a person fixed effect representing the fully portable component of wage capacity of individual i, and $\boldsymbol{X}'_{it}$ is a set of time-varying controls.[44] The relation to my search model is $\alpha_{it} = \alpha_i + X'_{it}\beta$, that is, the two terms on the right hand side capture the wage an individual is paid by every employer equally. $\psi_{\boldsymbol{J}(i,t)}$ is the wage premium paid by employer j to every worker. $\boldsymbol{J}(i,t)$ indicates the workplace for worker i in year t, and r_{it} is the residual. I estimate equation 3 separately for the 1996–2003 and 2004–2011 panel (columns 2 and 4 in Table 1), where I rely on the procedure by Kline et al. (2020) to calculate the (co)variances of the person and firm effects.[45]

Table 3: AKM VARIANCE ESTIMATES

	1996–2003	2004–2011
Variance of person effect	0.1538	0.1568
Variance of firm effect	0.0142	0.0127
Covariance of person and firm effect	0.0055	0.0055
Number of movers	118,942	153,418

Notes: This table reports the (co-)variances of person and firm effects from estimating the AKM wage regression using the procedure by Kline et al. (2020) on the samples in columns 2 and 4 of Table 1. See Tables A.7 and A.8 for a full decomposition of wage variance.

Table 3 summarizes the variation in worker and employer wage effects in the 1996–2003 and the 2004–2011 panel. Variance in person effects explains the largest share of variance in

[43] A similar picture is obtained for the 1996–2003 sample (Figure A.8).

[44] The person fixed effect and the time-varying terms in X are only identified under a normalizing assumption. Following Card et al. (2018) I assume that $X'_{it}\beta = 0$ at age 40, that is, the person effects are measured as of age 40.

[45] (Co)variances of the person and firm effects when calculated using the OLS point estimates suffer from a bias due to sampling error, often referred to as *limited mobility bias* (Krueger and Summers, 1988; Andrews et al., 2008). Appendix G.2 provides details on the estiation of wage components.

wage, while variance in firm effects is one order of magnitude smaller. The covariance between person and firm effects is positive, reflecting that high-wage workers are sorted to high-wage firms.[46] In the following section, I show how we can combine the estimates from the AKM model with those from my search model to learn about job value inequality between workers, and about its evolution over time. Before that, I briefly discuss how the assumptions underlying the identification of equation 3 are reconciled with my search model.

Search Model and AKM When estimating equation 3, I assume that worker mobility is uncorrelated with the time-varying residual component of wages (see Card et al. (2013) for a detailed discussion of this assumption).[47] In my search model, however, workers are the more likely to move to an outside employer if the residual component of the wage offer made by the outside employer is higher. Nevertheless, I show in Appendix G.3 that under a condition on firm offer intensity, the identification assumptions of the AKM model are nested in my search model. Intuitively, the reason is that the AKM model identifies employer wage premia from *all* transitions between employers, including those with an interrupting non-employment spell, while my search model only uses *voluntary and direct* transitions between employers for identification.

4 The Evolution of Non-Wage Job Values and Implications for Inequality

I will now estimate the job value of each worker in my sample, and analyze its distribution in the 1996–2003 and the 2004–2011 panel. Guided by a simple model of a monopsonistic labor market, I will then provide evidence on changes in labor market fundamentals driving the observed evolution of job value over time.

[46]Comparing the estimates to recent estimates by Bonhomme et al. (2020) and Kline et al. (2020), I find a larger variance of the worker wage effect, while the variance of the firm effect and the covariance between worker and firm effect is smaller, suggesting that differences between firms are less important for wages in my sample (see Table A.6).

[47]I show in Appendix G.1 that there is no evidence that worker mobility is correlated with the time-varying residual component of wages.

Table 4: JOB VALUE VARIANCE 1996–2003 AND 2004–2011

	1996–2003 (1)	2004–2011 (2)	(2)-(1)
$Var(V_{ij})$	0.524	0.564	0.040
$Var(ln(w_{ij}))$	0.195	0.197	0.002
$Var(a_j + \epsilon_{ij})$	0.265	0.277	0.012
$2Cov(w_{ij}, a_j + \epsilon_{ij})$	0.064	0.090	0.026
$2Cov(\alpha_i, a_j)$	0.075	0.082	0.007
$2Cov(\psi_j, a_j)$	-0.015	0.006	0.021

Notes: This table reports the variance of job value, and covariances of job value components in the 1996–2003 sample and in the 2004–2011 sample. The variance-covariance matrix of all job value components is reported in Appendix Table A.7 and A.8.

4.1 The Distribution of Job Value 1996–2003 and 2004–2011

Estimating Job Value Under the assumptions of my search model, each worker employed at a firm in my sample receives the following job value:

$$V_{it} = ln(w_{it}) + ln(a_{\boldsymbol{J}(i,t)}) + \epsilon_{it} \tag{4}$$

where I observe worker i's wage in year t, $ln(w_{it})$, in the data and estimate the non-wage value of his current firm, $ln(a_{\boldsymbol{J}(i,t)})$, in my search model. I do not observe the realization of ϵ_{it}, but I can obtain an estimate of its distribution from my search model.[48] I estimate the job value of each person-year observation in the 1996–2003 and 2004–2011 panel (columns 2 and 4 of Table 1) using the corresponding search model estimates.

The Distribution of Job Value Table 4 shows, in the first row, the variance of job value among person-year observations in the 1996–2003 and the 2004–2011 panel. We see that inequality in job value among workers, when measured through the variance, increased by 7.6 percent from 1996–2003 to 2004–2011.

[48] I know the distribution of ϵ_{it} across offered jobs, which is $\epsilon_{it} \sim N(0, \hat{\sigma}^2)$ and can thus use this distribution in the variance decomposition. By doing so, I ignore the fact that the distribution of ϵ_{it} among accepted job-offers is truncated from below, and has thus smaller variance, for workers either hired through an firm-to-firm transition, or workers hired otherwise that have received an outside job-offer in the meantime. I ignore this because I cannot observe outside job-offers. My estimates of the variance of ϵ_{it} among accepted job-offers should thus be seen as an upper bound. In Appendix H I derive a lower bound on the variance of ϵ_{it}. The only result that is affected by this is the share of job value variance that is due to non-wage value, which decreases to 54 percent in both periods.

To understand the drivers of this increase in inequality, note that

$$Var(V_{it}) = Var(ln(w_{it})) + Var(ln(a_{\boldsymbol{J}(i,t)}) + \epsilon_{it}) + 2Cov(ln(w_{it}), ln(a_{\boldsymbol{J}(i,t)}) + \epsilon_{it}) \quad (5)$$

that is, the variance in job value can be decomposed into wage variance, variance in non-wage value, and the covariance between wage and non-wage value. Rows 2-4 of Table 4 show how these components contribute to total job value variance. We see that in both periods of the panel around 35 percent of job value variance stems from variance in wage, around 50 percent from variance in non-wage value, and the rest from the covariance between wage and non-wage value. The variance in wage is almost the same in both periods, reflecting the very stable wage structure in Austria between 1996 and 2011. The variance in non-wage value increased slightly from 1996–2003 to 2004–2011, contributing about one third to the increase in total job value variance between the two periods.

The other two thirds of the increase in job value inequality are attributable to the increase in covariance between wage and non-wage value, as shown in the 4th row of Table 4. The covariance between wage and non-wage value is positive in both periods, reflecting sorting of workers with high wages to firms offering high non-wage value. The increase in the covariance thus shows that this sorting got stronger over time. Graphically, this can be seen in Figure 5, which shows the distribution of non-wage value with workers grouped by decile of the wage distribution. We see a particularly strong downward shift in the non-wage value distribution for workers in the lowest wage decile from 1996–2003 to 2004–2011. At the same time, the distribution of non-wage value for workers with above-median wage shifted slightly upwards. Both together explain the increase in covariance between wage and non-wage value between 1996–2003 and 2004–2011.

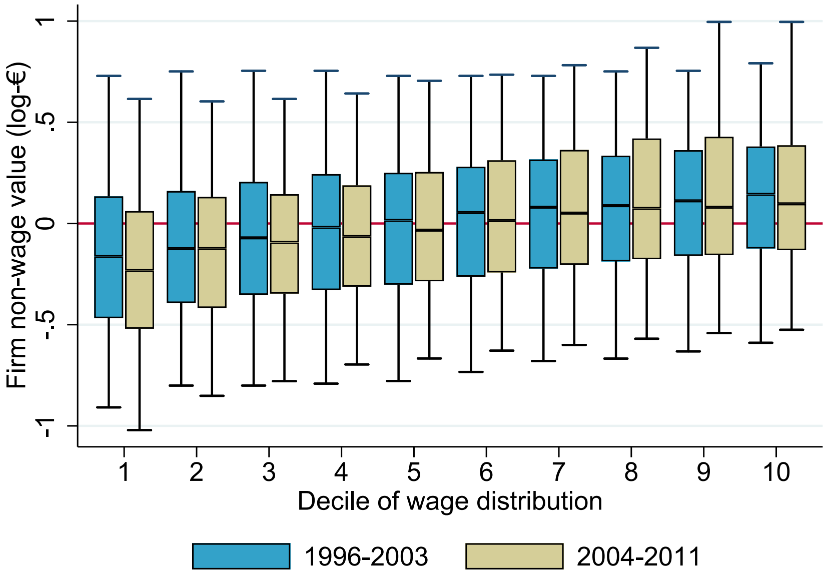
Additional insights into the increase in job value inequality can be gained by examining the covariance between non-wage value and the AKM components of wage, that is,

$$\begin{aligned} Cov(ln(w_{it}), ln(a_{\boldsymbol{J}(i,t)}) + \epsilon_{it}) = Cov(\alpha_i, ln(a_{\boldsymbol{J}(i,t)})) &+ Cov(\psi_{\boldsymbol{J}(i,t)}, ln(a_{\boldsymbol{J}(i,t)})) \\ &+ Cov(\boldsymbol{X}'_{it}\beta, ln(a_{\boldsymbol{J}(i,t)})) \end{aligned} \quad (6)$$

where $Cov(\alpha_i, ln(a_{\boldsymbol{J}(i,t)}))$ measures the extent to which workers with different wage capacity are sorted among firms with respect to the non-wage value they offer. The row $Cov(\alpha_i, ln(a_{\boldsymbol{J}(i,t)}))$ of Table 4 shows that workers with higher wage capacity are sorted to firms offering higher non-wage value in both periods. While this sorting explains about 10 percent of overall job value inequality, it only increased slightly between 1996–2003 and 2004–2011.

$Cov(\psi_{\boldsymbol{J}(i,t)}, ln(a_{\boldsymbol{J}(i,t)}))$ measures how firm non-wage value covaries with firm wage pre-

Figure 5: Non-Wage Values by Wage Decile



Notes: This figure shows non-wage values of workers' firms, by decile of the wage distribution. The box ranges from the 1st to the 3rd quartile of the firm non-wage value distribution in the respective decile. The whiskers range from the 5th to the 95th percentile of the firm non-wage value distribution in the respective decile.

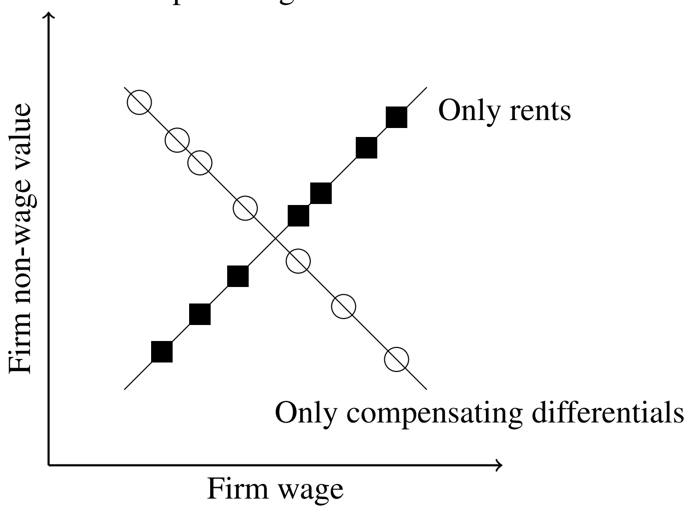
mium. Figure 6 a shows how the relationship between $\psi_{\boldsymbol{J}(i,t)}$ and $ln(a_{\boldsymbol{J}(i,t)})$ can be interpreted as evidence for compensating differentials and rents. Intuitively, if there is no variation in rents that firms offer and firms fully compensate through wage for the quality of their non-wage characteristics, firm wage and non-wage value will be perfectly negatively correlated. If there are no compensating differentials and dispersion of wage and non-wage value is purely due to firms offering rents, firm wage and non-wage value will be perfectly positively correlated. The covariance of firm wage and non-wage value thus represents the sum of these two effects.

A negative value of $Cov(\psi_{\boldsymbol{J}(i,t)}, ln(a_{\boldsymbol{J}(i,t)}))$ implies compensating differentials have an attenuating effect on job value inequality. A positive value of $Cov(\psi_{\boldsymbol{J}(i,t)}, ln(a_{\boldsymbol{J}(i,t)}))$ implies that job value inequality is exacerbated by firm-level rents. As shown in Figure 6 b and the last row of Table 4, there is a striking difference between $Cov(\psi_{\boldsymbol{J}(i,t)}, ln(a_{\boldsymbol{J}(i,t)}))$ in 1996–2003 and 2004–2011. While it is substantially negative in 1996–2003, it is slightly positive in 2004–2011.[49] Thus, compensating differentials had a substantial inequality attenuating effect in 1996–2003, but this effect vanished and is dominated by increased dispersion in firms' job

[49]Figure A.3 describes the underlying change in the relationship between employer-to-employer transitions and employer wage premium. From 1996–2003 to 2004–2011, the relationship between a firm's number of hires relative to its quits and the wage gain of its hires relative to that of its quits became considerably stronger, indicating that firms offering higher wage were considered more attractive by workers in 2004–2011 than in 1996–2003.

Figure 6: RELATION OF FIRM WAGE & FIRM NON-WAGE VALUE

(a) Theoretical: Compensating Differentials and Rents



(b) Empricial: Compensating Differentials and Rents 1996–2003 and 2004–2011

Notes: Figure a shows the theoretical relationship between firm wage and firm non-wage value in two limit cases; 1., when there is full compensation between firm wage and firm non-wage value and thus no rent dispersion, and 2., when there is no compensation between firm wage and firm non-wage value and thus all of firm wage and firm non-wage value is rents. Figure b shows a scatterplot of the actual distribution of firm wage and firm non-wage value in 1996–2003 and 2004–2011. The lines in Figure b represent an OLS regression of firm non-wage value on firm wage, with firms weighted by the number of people-years they represent.

value offers by 2004–2011. This explains more than half of the overall increase in job value inequality between 1996–2003 and 2004–2011.[50]

[50]Changes to the components of job value variance not reported in Table 4 only have a minor impact on the evolution of job value inequality between 1996–2003 and 2004–2011. The full variance-covariance matrices of job value components can be found in Table A.7 and A.8.

4.2 Why Did Job Value Inequality Increase?

I will now discuss potential explanations for the increase in job value inequality caused by changes in firms' wage and non-wage value offer. These explanations should account for the following two empirical results: First, for the increase in $Var(a_j + \psi_j)$, that is, the increase in dispersion of value offered by firms. Second, for the increase in $Cov(a_j, \psi_j)$, reflecting the disappearance of compensating differentials. Lang and Majumdar (2004) show that these two can be considered separately. Intuitively, the firm's problem consists of a stage where it chooses which value to offer, and a stage where it best allocates value between wage and non-wage value (see Appendix I).

Increase in Firm Value Dispersion Because of search frictions and idiosyncratic preferences of workers over firms, firms in my search model face a labor supply that is upwards sloping in the firm value they offer.[51] My search model thus represents a standard monopsony framework as depicted in Figure 7 a.[52] Figure 7 a shows two firms: one with high marginal revenue product of labor (MRPL), and one with low MRPL, both facing the same labor supply curve. Figure 7 a shows that the high MRPL will maximize profits by offering a higher firm value than the low MRPL firm. Thus, dispersion of firm value can arise due to differences in MRPL across firms.

As we can see from Figure 7 a, the increase in dispersion of firm value offer I find in Austria can be explained by changes in the slope or location of either, the labor demand or labor supply curves. In particular, it can also be explained by a decrease in labor supply elasticity, as illustrated in Figure 7 b by the increased slope of the labor supply curve. Intuitively, the high MRPL firm has a greater incentive to increase its value offer in response to a decrease in labor supply elasticity as it has greater opportunity costs of losing workers and scaling down production (formal derivation in Appendix I.2). I will now evaluate whether there is evidence for a decrease in labor supply elasticity between 1996–2003 and 2004–2011.

The elasticity of labor supply is decreasing in the degree of search frictions in the labor market (Burdett and Mortensen, 1998).[53] I estimate the intensity with which workers receive outside job offers and find no evidence for an increase in search frictions (Table A.10). Another potential reason for a decrease in labor supply elasticity is that labor markets become less segregated, that is, it becomes more likely that workers at high-value firms receive offers from

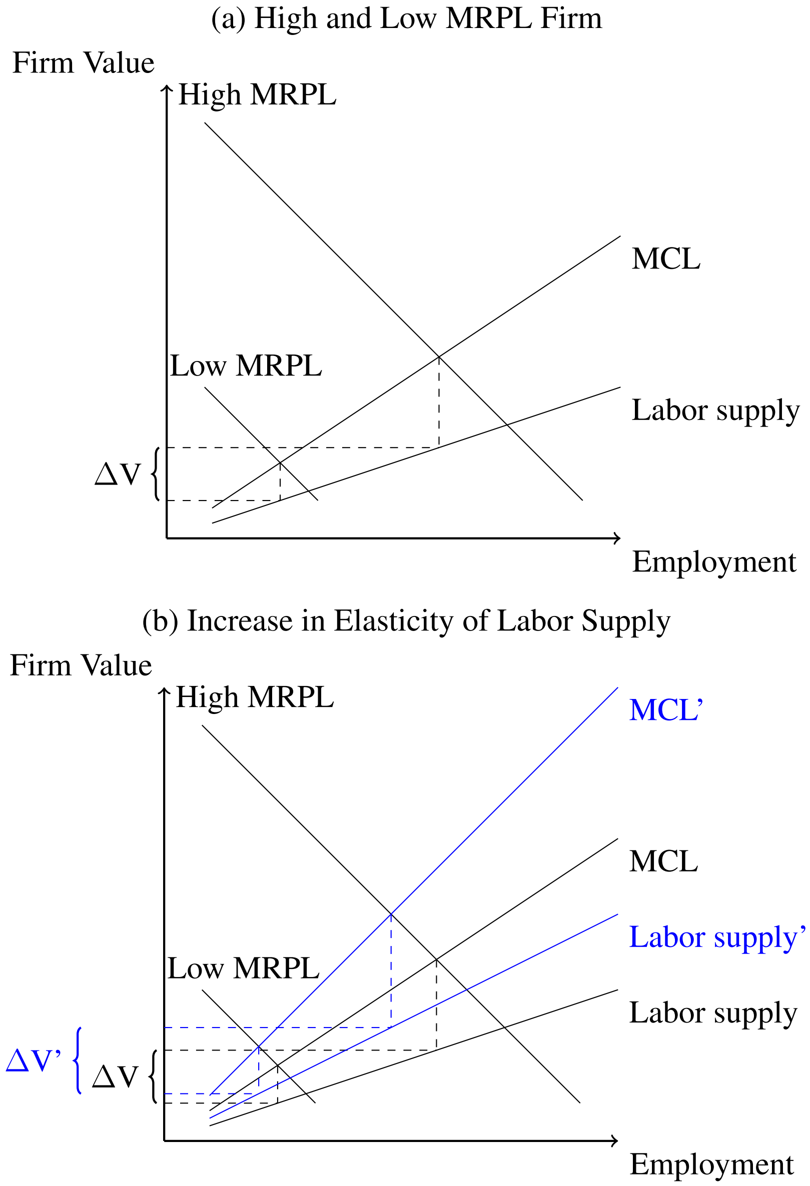
[51] Firm value = firm wage + firm non-wage value.

[52] This figure is inspired by Manning (2021, Figure 1).

[53] To see this, consider the case where there are no search frictions, that is, workers can instantaneously choose over the full set of firms in the labor market. This will result in perfectly elastic labor supply (absent idiosyncratic preferences). On the other hand, if there are infinite search frictions, thus workers never receive job offers from outside firms, labor supply to the firm becomes perfectly inelastic (see Appendix I.3).

low-value firms and vice versa (Berger et al., 2022).[54] I find no evidence that labor markets became less segregated between 1996–2003 and 2004–2011 (Table A.11).

Figure 7: LABOR SUPPLY AND DEMAND UNDER MONOPSONY



Notes: $V = \phi + ln(a)$; MRPL, marginal revenue product of labor; MCL, marginal cost of labor. Figure a illustrates the firm values offered by a firm with high MRPL and a firm with low MRPL, in a model with finite elasticity of labor supply. Figure b illustrates the effect of a decrease in labor supply elasticity on the profit-maximizing firm value offer of the high MRPL and the low MRPL firm.

The third reason why the labor supply elasticity could decrease is an increase in the idiosyn-

[54]Consider the case where a worker faces the binary choice between a firm A and an outside firm. The more different the outside firm's job value offer, the less firm A's labor supply depends on its own job value offer, because the marginal probability gain in the worker's binary choice from an increase in its own job value offer is lower (see I.4).

crasy of workers' preferences over firms (Card et al., 2018; Lamadon et al., 2021; Manning, 2021).[55] My search model provides me with an estimate of the variance of workers' idiosyncratic preferences over firms. The variance of workers' idiosyncratic preferences over firms increased by 8 percent from 1996–2003 to 2004–2011. Can thus a decline in labor supply elasticity fully account for the increase in job value dispersion I find? Figure 7 shows that for this to be plausible, there should be two patterns observable in the data: first, firms offering high value in 1996–2003 (high MRPL firms) should have seen a relative decline in employment from 1996–2003 to 2003–2011. Second, large firms (high MRPL firms) should have seen a relative increase in the job value they offer, relative to smaller firms. I observe a decline in employment at high value firms between 1996–2003 and 2004–2011, but do not find that large firms increased their value offer (Table A.12).

Thus, while a decline in labor supply elasticity can account for part of the increase in value dispersion among firms, there must also have been changes in labor supply or labor demand in a way that increases job value dispersion. I can only provide suggestive evidence on this.[56] I use the share of workers with foreign nationality in a firm or a local labor market as a proxy for an, at least in part, exogenous labor supply shifter. I find that the share of workers with foreign nationality increased more between 1996–2003 and 2004–2011 in firms offering low value in 1996–2003, and that firm value decreased more between 1996–2003 and 2004–2011 in firms where the share of workers with foreign nationality increased more between 1996–2003 and 2004–2011 (Table A.13). This suggests that changes to firm-specific labor supplies also contribute to explaining the increase in dispersion of employer value between 1996–2003 and 2004–2011.

Disappearance of Compensating Differentials The increase in $Cov(a_j, \psi_j)$ I find, reflecting the disappearance of compensating differentials, can be explained by changes in firms' marginal cost of non-wage value provision (Rosen, 1986). For example, compensating differentials could disappear if the marginal cost of non-wage value provision declined in firms that compensate for low non-wage value by paying high wage premia. I cannot directly test this, as I do not know what the cost of non-wage value provision is for firms. However, I show in Appendix I.6 that I can infer firms' marginal cost of non-wage value provision by assuming that firms allocate the value they provide between wage and non-wage value in a cost-minimizing way. I find that the marginal cost of non-wage value provision declined most between 1996–

[55]Consider the case where a worker faces the binary choice between a firm A and an outside firm. Increasing idiosyncratic preferences implies that the same increase in job value offer by firm A will lead to a smaller gain in probability the worker will choose firm A over the outside firm.

[56]I do not have any information available related to firms' MRPL function.

2003 and 2004–2011 in the construction and the real estate services industry, where firms compensate workers for low non-wage value through a wage premium (Figure A.4). This supports the explanation that firms that compensated for low non-wage values through high wage premia in 1996–2003 increased their non-wage value offer by 2004–2011, because it got cheaper for them to do so.

4.3 Relation to Literature

The evidence presented in this section echoes several findings from the literature on wage differentials between industry and firms, and on compensating wage differentials. Pierce (2001) and Maestas et al. (2018) show that various non-wage characteristics are better for workers earning higher wages, which is consistent with the positive correlation between the person wage effect and the non-wage value I find. Krueger and Summers (1988) find that industry wage premia cannot be explained as compensating differentials for non-wage characteristics, which is consistent with the close to zero correlation between firm wage and firm non-wage value I find for 2004–2011.[57] Hall and Mueller (2018) estimate the non-wage values of jobs offered to unemployed job seekers. They find a correlation of $-.17$ between the wage and non-wage value of jobs, close to the correlation of $-.12$ between firm wage and non-wage value I find for 1996–2003.[58] Taber and Vejlin (2020) find that 51 percent of the variance in workers' flow utility is explained by non-wage values, where I find that 57 percent of workers' job value variance is explained by non-wage values.[59]

Hamermesh (1999) shows that, over time, non-wage values can evolve differentially along the wage distribution because of income effects, that is, workers use their productivity gain over time differentially to buy higher wage or higher non-wage value. This channel is not at work in my study because the Austrian wage structure remained almost constant 1996–2011. I add to the findings of Hamermesh (1999) by showing that inequality in non-wage compensation can also change over time because of increased search frictions, changes in labor demand and supply, and changes in the cost of non-wage value provision for firms.

[57] Katz et al. (1989) find a slightly stronger positive correlation between industry pay premia and the quality of non-wage characteristics.

[58] Table A.9 compares the parameters I identify with those identified by Hall and Mueller (2018) and Taber and Vejlin (2020).

[59] For both, 1996–2003 and 2004–2011 I find that 57 percent of job value variance is explained by non-wage value, which I calculate as $\frac{Cov(ln(a_j)+\epsilon_{it},V_{it})}{Var(V_{it})}$. This can be compared to the estimate by Taber and Vejlin (2020) to the extent that non-wage value in my model is driven by instantaneous non-wage value flows, and not by expectations about future wage and non-wage value flows.

5 Robustness

The validity of this study also depends on the extent to which mechanisms not captured by my search model can account for the observed pattern of mobility between employers. I will now present evidence addressing concerns that my results are driven by preference heterogeneity, firm-specific skills, labor market learning, or my assumption on the process generating employment offers.

Offer Generating Process An arguably strong assumption of my model is that all firms direct an identical share of employment offers to non-employed workers, which implies that employed workers on average receive offers from the same distribution as non-employed workers. This assumption allows me to estimate the distribution of offers across firms that employed workers face, from where non-employed workers get hired. An alternative assumption on how firms direct offers is that every job is first offered to an employed worker, and if and only if the employed worker rejects the offer, the job is offered to a non-employed worker. If offers are generated following this process, I can estimate the offer distribution employed workers face from the number of workers a firm hires from both, employment and non-employment.

Estimating the model under this alternative assumption on the offer generating process, I obtain non-wage values very similar to my baseline estimates (Table A.14). To further confirm that my results are not driven by the assumption on the offer generating process, I estimate the model under the naive, and deliberately unrealistic, assumption that all firms are of equal size and make equally many offers. Even holding firm size and the number of offers constant across employers does not change any of my results regarding job value inequality. I thus conclude that the assumption on the offer generating process does not drive my results.

Preference Heterogeneity and Match-Specific Amenities Preference heterogeneity, that is, different workers *perceive* the value of the set of amenities they are offered by a particular firm differently, and match-specific amenities, that is, different workers *are actually* offered a different set of amenities by a particular firm, have the same implications for my model. I will thus in the following discussion only refer to preference heterogeneity, noting that the discussion and the provided evidence directly applies to match-specific amenities as well.

Preference heterogeneity over firms' non-wage characteristics is allowed for in my model by the idiosyncratic component of worker utility. My model does, however, not account for potential systematic preference heterogeneity between groups of workers. If there is systematic preference heterogeneity over firms' non-wage value between groups that are compared, assuming common preferences when identifying firms' non-wage value may lead to biased results. To see this, suppose that low-wage workers prefer working in low-wage industries, while high-wage workers equally strongly prefer working in high-wage industries. Estimating my model with these preferences would then result in firms' non-wage value being some weighted average of high-wage and low-wage workers' preferences. This would potentially lead me to infer differences in non-wage values between high-wage workers and low-wage workers, while both actually perceive the same non-wage value at their firms.

If preference heterogeneity between high and low-wage workers is important, we should observe different mobility patterns of high-wage workers compared to low-wage workers. As a result, my model should, when it is estimated using employer-to-employer transitions of workers with wages *above* the median, identify different non-wage values than when it is estimated using employer-to-employer transitions of workers with wages *below* the median.[60] However, this not the case. I conclude that systematic preference heterogeneity does not have an important impact on my results (Table A.15).

Labor Market Learning Another alternative explanation for mobility patterns between employers is that transitions are the result of employers learning about worker quality, rather than the arrival of an offer and a worker's choice.[61] My framework accounts for some forms of labor market learning: To the extent that labor market learning is the same across firms, it is accounted for by workers' idiosyncratic non-wage value draw. Labor market learning that leads to a layoff is accounted for in my model if the layoff either leads to an unemployment spell, or to a reduction in a firm's number of employees.

Nevertheless, it is still possible that labor market learning partly drives employer-to-employer mobility in my sample. Labor marker learning has been shown to be quite quick (Lange, 2007). Thus, if learning were important, we should observe different mobility patterns among young workers, where employers learn a lot about worker quality, as opposed to among old workers, where employers no longer learn much about worker quality. I test for this by splitting the sample of workers at the median worker age, and compare model estimates obtained with young

[60]To test this, I would ideally estimate firms' non-wage values separately using the sample of high and low-wage workers and compare them. This is not possible, however, because different firms are strongly connected in the sample of high and low-wage workers (recall that firms' non-wage values are only identified within the strongly connected set). I can, however, estimate my model using transitions of low-wage workers between firms strongly connected by transitions of low-wage workers, and check whether I obtain similar non-wage values when adding transitions of high-wage workers between these firms to the sample. I thank Mitch Downey for suggesting this approach.

[61]Sorkin (2018, 1385–1386) provides a thorough discussion of asymmetric learning and its implications for employer-to-employer mobility. Examples of markets where learning is important include academia (assistant professor tenure track) or law firms (the best will be promoted to partner, the others leave).

and old workers. I find that non-wage values are highly correlated, and thus I conclude that labor market learning is unlikely to affect my results (Table A.15).

Firm-Specific Human Capital A potential concern is that workers acquire firm-specific human capital over time, leading them to earn an idiosyncratic compensation premium at their current firm, which they are not offered by outside firms. Firm-specific human capital would thus violate the assumption of my model that firms offer the same wage and non-wage value to both, current and outside workers. If firm-specific human capital were to drive my model estimates of non-wage values, then the probability a worker accepts a job offer from an outside firm should decline when the worker acquires human capital, that is, with increasing tenure. In particular, the decline should be stronger for firms that I estimate to offer high non-wage value. Figure A.5 presents a test of this prediction at the industry level. I find no evidence that firm-specific human capital is related to my estimate of non-wage values.[62]

Overall, the robustness checks show that my assumption on the offer generating process does not drive my results. I also find no evidence that preference heterogeneity, match-specific amenities, asymmetric labor market learning, or firm-specific human capital have a relevant impact on my results.

6 Conclusion

The aim of this article is to estimate non-wage values of jobs, and show how the distribution of non-wage values among workers affects labor market inequality. I develop a labor market search model in which workers value both wage and non-wage value of jobs. I estimate the model using a large sample of full-time workers in Austria for the periods 1996–2003 and 2004–2011.

The key finding is that job value dispersion increased over time, in spite of a stable wage structure. The main reason is that compensating wage differentials, attenuating job value inequality, lost importance, while rents, exacerbating job value inequality, became more important. This finding is likely to be relevant for other developed countries, as many of its potential driving forces, such as industry-specific changes in the cost of non-wage value provision, are more likely to be a global phenomenon than to be specific to the Austrian labor market. At minimum, my findings show that non-wage value of jobs should be considered when monitoring inequality in the labor market, and when designing policies aimed at mitigating it.

[62]The only industry with a markedly distinct pattern in the probability a worker makes a firm-to-firm transition is the *Services*-industry. However, the decline as a function of tenure is *steeper* than in the other industries, while firms in *Services* offer *low* non-wage value.

The parsimonious model I develop allows for a tractable mapping of non-wage value estimates to descriptive evidence on wage differentials and worker flows. The flip-side is that my model does not incorporate features like systematic forms of preference heterogeneity over firms' non-wage values, or asymmetric learning in the labor market. While I provide evidence that these caveats are unlikely to alter my conclusions regarding job value dispersion and inequality, it might be desirable to enrich the model to incorporate some of these features in future studies.[63] Fruitful avenues could be the study of non-wage value differences from employer switches around events such as child birth or involuntary job loss.

[63]An interesting approach would be to combine the model with search frictions with features of Lamadon et al. (2021), who model the labor market without search frictions but with persistent preference heterogeneity over employers' amenities.

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A Additional Tables and Figures

Table A.1: INDUSTRY-LEVEL VARIATION IN FULL-TIME WORKERS' WEEKLY HOURS

	1996 – 2003					2004–2011				
	Mean	Sd	Median	P10	P90	Mean	Sd	Median	P10	P90
Industry										
Manufacturing	39.9	4.3	39.0	38.0	40.0	41.6	5.4	40.0	38.5	50.0
Utilities	39.8	3.1	40.0	38.0	40.0	42.5	6.2	40.0	38.5	50.0
Construction	40.3	4.4	40.0	38.0	40.0	42.0	5.7	40.0	38.5	50.0
Retail trade, cars	41.1	6.1	40.0	38.0	46.0	42.2	6.2	40.0	38.5	50.0
Transportation	41.4	5.8	40.0	38.0	45.0	43.8	7.4	40.0	40.0	55.0
Hotel and restaurant	44.4	9.9	40.0	38.0	60.0	44.1	8.8	40.0	40.0	55.0
Information and communication	41.4	6.0	40.0	38.0	50.0	43.5	6.3	40.0	38.5	50.0
Finance and insurance	40.0	4.7	39.0	38.0	40.0	43.0	6.3	40.0	38.5	50.0
Real estate	41.2	5.6	40.0	38.0	44.0	42.8	7.4	40.0	38.5	50.0
Prof./scientific/tech. services	42.9	7.9	40.0	38.0	55.0	43.6	7.0	40.0	38.5	53.0
Services	40.9	5.4	40.0	38.0	40.0	42.2	6.3	40.0	38.5	50.0
Public admin./education	40.4	3.3	40.0	38.0	40.0	42.9	6.6	40.0	40.0	50.0
Health and social	41.3	5.7	40.0	38.0	45.0	42.8	7.6	40.0	38.5	50.0
Observations			691,247					393,278		

Notes: This table reports summary statistics on weekly working hours of full-time workers by industry, estimated using data from the Austrian Mikrozensus. Summary statistics are calculated using inverse probability weights provided by Statistics Austria. I classify a worker as full-time worker if he is not self-employed and reports working at least 36 hours in a normal work week. A major reform of the Mikrozensus in 2004, including a change in definition of employment status limits comparability of working hours before 2004 and after 2004 (Lehmann, 2019).

Table A.2: Employment Spells Ending 1996–2003 & 2004–2011

	1996 – 2003		2004–2011	
	Count	**Annual Hazard**	**Count**	**Annual Hazard**
	(1)	(2)	(3)	(4)
Employment spells ending	1,279,886	0.1634	1,297,070	0.1613
Thereof due to				
Firm rename	243,281	0.0311	279,780	0.0348
Firm takeover	1,198	0.0002	762	0.0001
Firm spin-off	191	0.0000	128	0.0000
Firm closure	127,772	0.0163	117,511	0.0146
Spells ending excluding those due to firm-level event	907,444	0.1158	898,889	0.1118
Thereof				
Employer-to-Nonemployment transitions	504,118	0.0644	510,475	0.0635
All Employer-to-Employer transitions	403,326	0.0515	388,414	0.0483
Thereof				
new job < 1 calendar year or not full time	244,127	0.0312	209,579	0.0261
Employer-to-Employer transitions (full-time & full year)	159,199	0.0203	178,835	0.0222
Thereof				
Involving firm not in strongly connected set	100,850		104,564	
Employer-to-Employer transitions in SC set	58,349	0.0157	74,271	0.0168
Employer-to-Employer transitions in SC set (weighted)	26,931	0.0072	39,426	0.0089

Note: This table shows how I obtain my sample of employer-to-employer transitions from all employment spells that end in my sample of strongly connected firms. Annual Hazard as (number of transitions)/(number of person-year observations). Definition of firm rename, takeover, spin-off, and closure in Appendix B. *Employer-to-Nonemployment*: Employment spells ending with a layoff or with at least 30 days of non-employment after the spell ends. *Employer-to-Employer (full-time & full year)*: All employer-to-employer transitions satisfying the definition in Section 2. *Employer-to-Employer in SC set (weighted)*: All employer-to-employer transitions between firms in the strongly connected set, after reweighting transitions at contracting firms using the procedure described in Section 2.

Table A.3: BY INDUSTRY – EMPLOYER-TO-EMPLOYER TRANSITION RATES AT EXPANDING EMPLOYERS

	1996–2003	2004–2011
Manufacturing	0.009	0.009
Utilities	0.005	0.007
Construction	0.011	0.012
Retail trade, cars	0.012	0.012
Transportation	0.014	0.014
Hotel and restaurant	0.009	0.009
Information and communication	0.021	0.018
Finance and insurance	0.012	0.012
Real estate	0.012	0.012
Prof./scientific/tech. services	0.014	0.016
Services	0.017	0.031
Public admin./education	0.006	0.008
Health and social	0.012	0.010
Arts and entertain.	0.006	0.007

Notes: This table reports the annual probability a worker in the sample makes a employer-to-employer transition as defined in section 2, at firm-years with employment growth ≥ 0.

Table A.4: BY INDUSTRY – NUMBER OF HIRES AND QUITS 2004 – 2011

	Unweighted		Layoff weighted	
	Hires (1)	Quits (2)	Hires (3)	Quits (4)
Manufacturing	24,195	18,007	12,659	10,256
Utilities	2,090	1,087	1,034	580
Construction	4,795	5,837	2,365	2,553
Retail trade, cars	7,737	8,617	4,193	4,425
Transportation	6,512	6,201	3,049	3,120
Hotel and restaurant	247	369	137	178
Information and communication	5,707	4,971	2,106	2,083
Finance and insurance	5,560	5,157	3,050	2,739
Real estate	913	2,103	601	686
Prof./scientific/tech. services	4,614	6,103	2,529	2,220
Services	4,830	9,884	2,600	6,434
Public admin./education	5,523	4,120	4,025	3,140
Health and social	1,163	1,463	840	806

Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for the 2004–2011 sample. Columns 1 and 2: Number of hires and quits in sample by industry. Columns 3 and 4: Number of hires and quits by industry, after downweighting quits from contracting firms according to procedure explained in Section 2.

Table A.5: BY INDUSTRY – WAGES AND WAGE DIFFERENTIALS

	1996–2003 (1)		**2004–2011** (2)	
Median monthly wages by industry (2012 €)				
Manufacturing	3,365		3,569	
Utilities	3,432		4,103	
Construction	3,083		3,194	
Retail trade, cars	3,122		3,262	
Transportation	2,728		2,837	
Hotel and restaurant	2,187		2,240	
Information and communication	4,914		4,561	
Finance and insurance	4,506		4,900	
Real estate	3,233		3,450	
Prof./scientific/tech. services	3,783		4,244	
Services	2,909		2,938	
Public admin./education	2,780		3,081	
Health and social	2,927		3,163	
Δ *log-wage of employer-to-employer transitions*	Hires	Quits	Hires	Quits
Manufacturing	0.086	0.010	0.069	0.005
Utilities	0.011	0.022	0.035	0.029
Construction	0.037	0.015	0.054	0.021
Retail trade, cars	0.053	0.062	0.054	0.058
Transportation	0.004	0.044	0.023	0.045
Hotel and restaurant	-0.014	0.084	-0.011	0.079
Information and communication	0.121	0.106	0.059	0.048
Finance and insurance	0.089	0.081	0.075	0.072
Real estate	0.048	0.027	0.055	0.049
Prof./scientific/tech. services	0.066	0.094	0.069	0.086
Services	0.041	0.097	0.031	0.078
Public admin./education	-0.037	0.086	-0.020	0.083
Health and social	0.014	0.080	0.010	0.055

Note: This table reports wages and wage differentials by industry, using the sample of strongly connected firms (columns 2 and 4 of Table 1). The panel Δ *log-wage of employer-to-employer transitions* takes into account that wages at the old employer are observed in year t, and at the new employer in year $t+2$ by subtracting time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2). In the lower panel, transitions are weighted by their probability of being an excess separation as defined in the text in Section 2.

Table A.6: COMPARISON OF WAGE VARIANCE DECOMPOSITION WITH KLINE ET AL. (2020) AND BONHOMME ET AL. (2020)

	Own 1996–2003 (1)	Own 2004–2011 (2)	K. et al. (2020) (3)	B. et al (2020) (4)
var of log-wage†	0.190	0.193	0.184	0.182
share firm effect	0.073	0.065	0.130	0.129
share person effect	0.794	0.805	0.608	
share sorting	0.057	0.057	0.160	0.130
Corr(firm,person)	0.114	0.120	0.262	0.340

Notes: This table reports results from decomposing wage variance. The variance of log-wage is the variance net of time and experience effects, that is, var(log-wage net of time and experience) $= var(\alpha) + var(\psi) + 2 * cov(\alpha, \psi) + var(r)$. The person share is not reported by Bonhomme et al. (2020).
† After removing time/experience effects.

Table A.7: COVARIANCES OF JOB VALUE COMPONENTS 1996–2003

		Job value	Wage	Non-wage	Wage: Person	Wage: Employer	Wage: $X'_{it}\beta$	Wage: r_{it}	Non-wage: Employer	Non-wage: Idio.
	Job value	0.524								
	Wage	0.227	0.195							
	Non-wage	0.297	0.032	0.265						
Wage	Person	0.193	0.156	0.037	0.154					
Wage	Employer	0.012	0.020	-0.008	0.006	0.014				
Wage	$X'_{it}\beta$	0.007	0.005	0.002	-0.003	0	0.008			
Wage	r_{it}	0.015	0.015	0	0	0	0	0.015		
Non-wage	Employer	0.231	0.032	0.199	0.037	-0.008	0.002	0	0.199	
Non-wage	Idiosyncratic	0.066	0	0.066	0	0	0	0	0	0.066

Notes: This table reports covariances of job-value components in the 1996–2003 sample. The covariances are estimated using all person-year observations from Table 1 column 2, and the estimates on wage and non-wage value components from Section 3.3.

Table A.8: Covariances of Job Value Components 2004–2011

		Job value	Wage	Non-wage	Wage: Person	Wage: Employer	Wage: $X_{it}'\beta$	Wage: r_{it}	Non-wage: Employer	Non-wage: Idio.
	Job value	0.564								
	Wage	0.242	0.197							
	Non-wage	0.322	0.045	0.277						
Wage	Person	0.202	0.161	0.041	0.157					
Wage	Employer	0.021	0.018	0.003	0.006	0.013				
Wage	$X_{it}'\beta$	0.005	0.004	0.001	-0.001	0	0.006			
Wage	r_{it}	0.014	0.014	0	0	0	0	0.014		
Non-wage	Employer	0.250	0.045	0.205	0.041	0.003	0.001	0	0.205	
Non-wage	Idiosyncratic	0.071	0	0.071	0	0	0	0	0	0.071

Notes: This table reports covariances of job-value components in the 2004–2011 sample. The covariances are estimated using all person-year observations from Table 1 column 4, and the estimates on wage and non-wage value components from Section 3.3.

Table A.9: Comparison of Own Estimates with Hall and Mueller (2018) and Taber and Vejlin (2020)

	Own 1996–2003 (1)	Own 2004–2011 (2)	HM (2018) (3)	TV (2020) (4)
var of log-wage	0.20	0.20	0.24	0.12
share person	0.88	0.87	0.76	
var of non-wage value	0.26	0.28	0.12	
Corr(non-wage value, wage)†	-0.12	0.05	-0.17	
Var of job value	0.52	0.56		0.25
Share non-wage value	0.57	0.57		0.51

Notes: This table reports results from decomposing job value variance. Column 3 uses values reported in Table 2 in Hall and Mueller (2018), applying the following calculation (using the notation of Hall and Mueller (2018)): *var of log-wage* $= \sigma_y^2 + \sigma_x^2$; *share person* $= \frac{\sigma_x^2}{(\sigma_y^2+\sigma_x^2)}$; *var of non-wage value* $= \sigma_\eta^2 + \kappa^2 * \sigma_y^2$; *Corr(non-wage value, wage)* $= \frac{\kappa * \sigma_y^2}{\sqrt{(\sigma_\eta^2+\kappa^2*\sigma_y^2)}*\sigma_y}$. I calculate the values in Column 1 and 2 using the estimates reported in Table A.7 and A.8, where *share person* $= \frac{\text{var(person)}}{\text{var(wage)-2*cov(person,firm)}}$, and *Corr(non-wage value, wage)* $= \frac{\text{cov(non-wage value, wage employer)}}{\sqrt{\text{var(non-wage value)*var(wage employer)}}}$. Column is based on Table 6 and 7 in Taber and Vejlin (2020), including the residual variation in wage estimated by Taber and Vejlin (2020) (.02) for consistency with my estimates.

† After removing personal-specific components and wage residual.

Table A.10: LABOR MARKET FRICTIONS

	Offer intensity	Hazard
1996–2003 Panel	0.067	0.105
2004–2011 Panel	0.072	0.100

Note: This table reports the average offer intensity and annual hazard rate of employment spells among firms in my sample. The offer intensity is measured as the total number of hires from non-employment by firms in sample, divided by the number of people-years in sample. The hazard is measured as the number of employment spells that end in the sample period, divided by the number of people-years in sample.

Table A.11: LABOR MARKET SEGREGATION

	Difference in firm value offer							
	Accepted offers				Estimated offers			
	rescaled | Mean |	rescaled SD	| Mean |	SD	rescaled | Mean |	rescaled SD	| Mean |	SD
1996–2003	0.825	0.964	0.373	0.436	0.946	1.207	0.428	0.546
2004–2011	0.866	1.048	0.415	0.502	0.966	1.239	0.463	0.594

Note: This table reports summary statistics on the degree of labor market segregation in 1996–2003 and in 2004–2011. *Accepted Offers* shows the distribution of the absolute value of the firm value difference between the firm making the offer and the firm receiving the offer, among all employer-to-employer transitions (Panel D of Table 1). The columns *Estimated offers* show the distribution of the absolute value of the firm value difference between the firm making the offer and the firm receiving the offer, among all offers made, estimated as described in Appendix J. The prefix *rescaled* indicates that the value is divided by the standard deviation of total firm value, calculated as the standard deviation of firm value among firms, weighted by the number of people-years observations, in the respective sample period. The conclusion that segregation did not contribute to a decline in labor supply elasticity is based on the lack of a substantial increase in the measures of value difference in offers that are corrected for overall value dispersion in the respective panel.

Table A.12: TEST OF PATTERNS IMPLIED BY A DECREASE IN LABOR SUPPLY ELASTICITY

	Ln(employees)		Δ ln(employees) 94-03 to 03-12		Δ Value 94-03 to 03-12	
	(1) 96-03	(2) 03-11	(3) employers	(4) cells	(5) employers	(6) cells
Firm value 1996-2003	0.927***		-0.088***	-0.010		
	(0.045)		(0.020)	(0.214)		
Firm value 2004-2011		0.603***				
		(0.038)				
Ln(employees) 1996-2003					-0.029***	-0.011
					(0.006)	(0.021)
Person-years	4,513,833	5,480,901	7,239,585	9,994,734	7,239,585	9,994,734
Industry-Federal state cells				82		82
Firms	4,544	5,944	2,495	7 993	2,495	7 993
Std indep. var.	0.452	0.479	0.447	0.259	1.367	0.997

Notes: This table reports coefficients from bivariate regressions of the variable in the column header on the variable in the row. Column 1: Regression of the log of the average number of yearly employees 1996-2003 on the firm value 1996-2003. Column 2 same as column 1 for 2004-2011. Columns 3 and 4: Regression of the change in log-average number of yearly employees 1996-2003 to 2004-2011 on the firm value 1996-2003. Columns 5 and 6: Regression of the change in firm value 1996-2003 to 2004-2011 on the log-average number of employees 1996-2003. The observational unit in columns 3 and 5 is the firm, limiting the sample to firms belonging to the sample in the 1996–2003 and the 2004–2011 period. Columns 4 and 6 are based on a repeated cross section with firms aggregated on the federal state by industry level. Both regressions are weighted using the sum of the number of people-years in both periods as analytical weights.
* p<0.05, ** p<0.01, *** p<0.001

Table A.13: Firm Value and Δ Share Foreign Nationals

	Δ share foreigners 1996-2003 to 2004-2011		Δ firm value 1996-2003 to 2004-2011	
	(1)	(2)	(3)	(4)
Firm value 1996-2003	-0.015***	-0.026*		
	(0.002)	(0.014)		
Δ share foreigners 1996-2003 to 2004-2011			-0.552***	-1.563**
			(0.188)	(0.611)
Person-years	7,239,585	9,994,734	7,239,585	9,994,734
Industry-Federal state cells		82		82
Firms	2,495	7,993	2,495	7,993
Share foreigners 1996–2003	0.101	0.106	0.101	0.106
Share foreigners 2004–2011	0.132	0.140	0.132	0.140

Notes: This table reports regression results on the relationship between the change in workforce with foreign nationality and firm value. Columns 1 and 2 show results from regressing the change in the share of the workforce with foreign nationality on the firm value 1996–2003. Columns 3 and 4 show results from regressing the change in firm value 1996–2003 to 2004–2011 on the change in the share of the workforce with foreign nationality. Nationality is measured at labor market entry. The observational unit in columns 1 and 3 is the firm, limiting the sample to firms belonging to the sample in the 1996–2003 and the 2004–2011 period. Columns 2 and 4 are based on a repeated cross section with firms aggregated on the federal state by industry level All regressions are weighted using the sum of the number of people-years in both periods as analytical weights.
* p<0.05, ** p<0.01, *** p<0.001

Table A.14: Results From Estimating the Model Under Alternative Offer Intensities

	1996 – 2003			**2004–2011**		
	Non-emp. Hires	**All Hires**	**Constant**	**Non-emp. Hires**	**All Hires**	**Constant**
A. Summary Stats on Offers						
Mean # of offers per firm	60	119		59	123	
Std # of offers per firm	134	236		132	263	
Corr(Non-employment hires, all hires)	0.94			0.87		
B. Model Results						
Correlation firm wage, firm non-wage	-0.12	-0.13	-0.12	0.05	0.03	0.03
Correlation person wage, firm non-wage	0.21	0.19	0.18	0.22	0.21	0.20

Note: Panel A of this table reports summary statistics on offers made by firms to other firms' employees, when offers are estimated under two different assumptions on the process generating them. *Non-emp. Hires* refers to the baseline approach using all hires from non-employment to estimate firms' offer intensity. *All Hires* refers to the alternative approach of using all workers hired in the corresponding sample period to estimate firms' offer intensity. *Constant* keeps offer distribution and employer size constant across employers. Panel B reports the correlation of job value components obtained when estimating the model using the offer distribution indicated in the corresponding column.

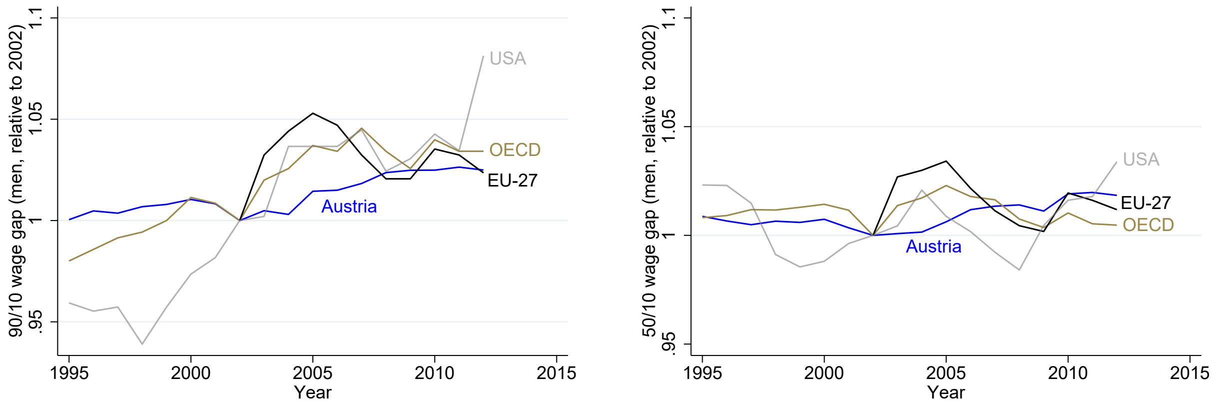
Table A.15: ROBUSTNESS – PREFERENCE HETEROGENEITY AND ASYMMETRIC LEARNING

	Estimate	Strongly connected	Transitions (Restricted)	Transitions (All)
Panel A: Preference Heterogeneity – Low-Wage vs. High-Wage Workers				
1996–2003				
Using low-wage workers' SC set				
Corr. low-wage's $ln(a)$, all's $ln(a)$	0.81	1,303	11,986	21,548
Corr. high-wage's $ln(a)$, all's $ln(a)$	0.89	1,792	25,697	36,135
Offer distributions				
Corr. low-wage's, high-wage's offer dist.	0.48			
2004–2011				
Using low-wage workers' SC set				
Corr. low-wage's $ln(a)$, all's $ln(a)$	0.87	2,092	18,775	34,660
Using high-wage workers' SC set				
Corr. high-wage's $ln(a)$, all's $ln(a)$	0.90	2,449	33,422	45,986
Offer distributions				
Corr. low-wage's, high-wage's offer dist.	0.63			
Panel B: Asymmetric Learning – Young vs. Old Workers				
1996–2003				
Using young workers' SC set				
Corr. young's $ln(a)$, all's $ln(a)$	0.95	2,908	30,316	46,417
Offer distributions				
Corr. young's, old's offer dist.	0.83			
2004–2011				
Using young workers' SC set				
Corr. young's $ln(a)$, all's $ln(a)$	0.95	4,012	42,841	60,344
Offer distributions				
Corr. young's, old's offer dist.	0.83			

Note: This table reports the correlation between firms' non-wage values from the model estimated using the restricted sample of workers and from the model estimated using the full sample of workers (weighted by the number of person-year observations), on the subsample of firms strongly connected by employer-to-employer transitions of workers from restricted sample. The statistic reported on *Offer distributions* is the correlation between the number of offers all firms in sample (columns 2 and 4 of Table 1) make to the two subgroups of Panel A and B of this table. The samples are split by median age/wage. Median age 1996–2003: 38.04; Median age 2004–2011: 40.30; Median monthly wage (2012 €) 1996–2003: 3048.13; Median monthly wage (2012 €) 2004–2011: 3195.62. Example of how to read the table: The 1st row *Corr. low-wage's $ln(a)$, all's $ln(a)$* shows that the firm non-wage value estimates estimated using transitions of low-wage workers, and the set of firms strongly connected by at least 5 transitions of low-wage workers, is .81 correlated with non-wage values estimated on the set of firms strongly connected by at least 5 transitions of low-wage workers, but using transitions of low-wage & high-wage workers. The 3rd row *Corr. low-wage's, high-wage's offer dist.* shows that the distribution from which high-wage workers are estimated to receive offers is .048 correlated with the distribution from which low-wage workers are estimated to receive offers (estimated using firms' hires from non-employment).

Figure A.1: 90-10 AND 50-10 WAGE GAP 1995–2012

(a) 90-10 Gap (b) 50-10 Gap

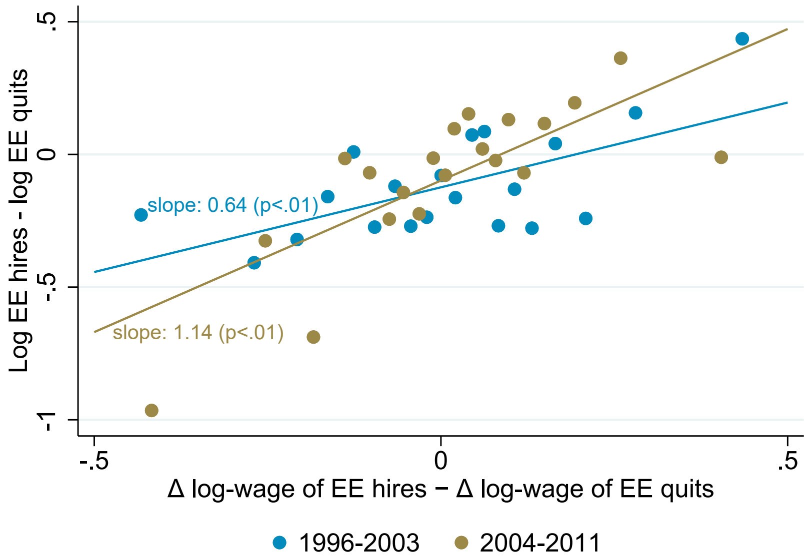


Notes: Figure a shows the gap between the 90th and the 10th percentile of the wage distribution in a given year for full-time working men. Figure b shows the gap between the 50th and the 10th percentile of the wage distribution in a given year for full-time working men. The gap is reported relative to the gap in year 2002.
Source: Austria: Own calculations; USA, EU-27 and OECD: OECD (2013).

Figure A.2: SHARE MEN EMPLOYED FULL-TIME 1995–2012

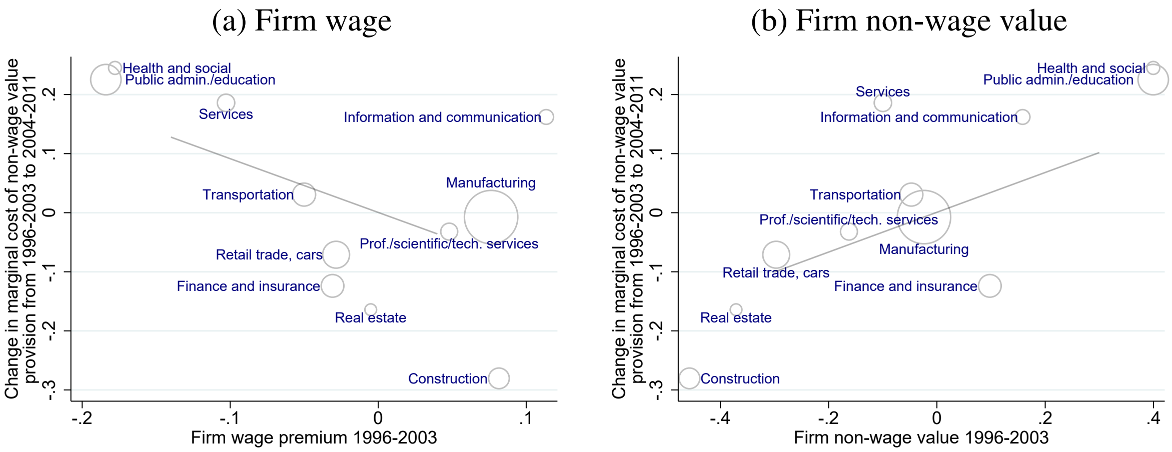
Notes: This figure shows the evolution of the share of all male workers in dependent employment that is working full-time. It is based on data from the Austrian Mikrozensus (Austrian labor force survey). I classify a worker as full-time employed if he reports working at least 36 hours in a normal work week. The discontinuity in year 2004 is due to a reform of the Mikrozensus, including change in definition of employment status, that was implemented in that year (Lehmann, 2019).

Figure A.3: DESCRIPTIVE EVIDENCE ON RELATIONSHIP BETWEEN EMPLOYER ATTRACTIVENESS AND EMPLOYER WAGE PREMIUM FROM 1996–2003 TO 2004–2011



Notes: This figure reports the relationship between the log of $\frac{\text{employer-to-employer hires}}{\text{employer-to-employer quits}}$ and the log of $\frac{\text{average wage increase of employer-to-employer hires}}{\text{average wage increase of employer-to-employer quits}}$. Firms for 1996–2003 (column 2 of Table 1) and 2004–2011 (column 4 of Table 1) are separately grouped into 20 firm-size (measured by the number of people-years) weighted bins by Δ log-wage of EE hires $-\Delta$ log-wage of EE quits. The regression lines represent the slope of an OLS regression, with firms weighted by the number of person-year observations they represent in the corresponding sample period. See Figure A.11 for version considering all workers and firms (columns 1 and 3 of Table 1.)

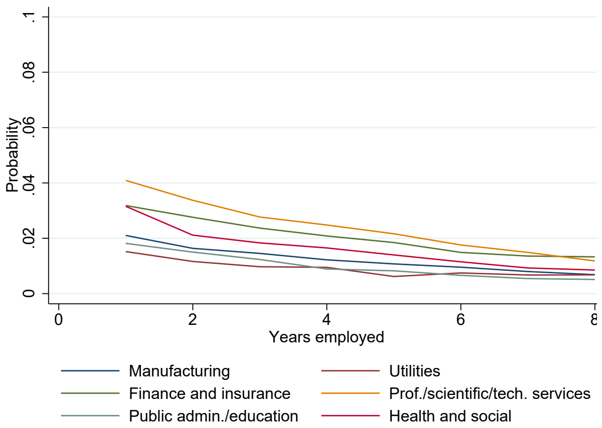
Figure A.4: CHANGE IN MARGINAL COST OF NON-WAGE VALUE PROVISION AND FIRM WAGE AND NON-WAGE VALUE



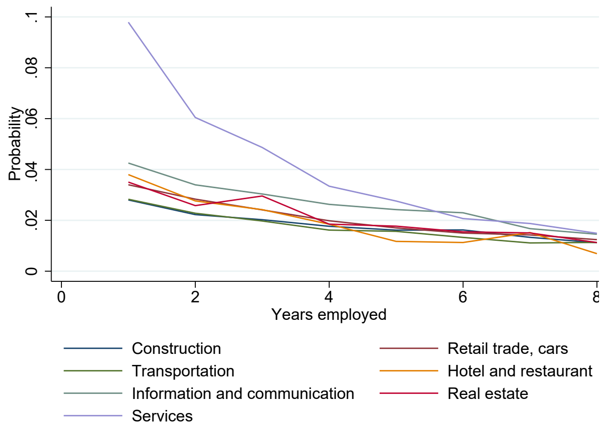
Notes: These figures show the difference between the industry-level average marginal cost of non-wage value provision for firms in the 2004–2011 panel and in the 1996–2003 panel, as a function of the firm wage premium and firm non-wage value in the 1996–2003 panel. The figure shows industry-level averages, which are calculated with firms weighted by the number of person-year observations they represent. The regression line represents a linear regression run at the industry-level, with industries weighted by the total number of person-year observations they represent in the 1996–2003 and the 2004–2011 panel. Marginal cost of non-wage value provision are derived as explained in Appendix I.6.

Figure A.5: ANNUAL PROBABILITY OF EMPLOYER-TO-EMPLOYER TRANSITION BY TENURE AND INDUSTRY, 1996–2011

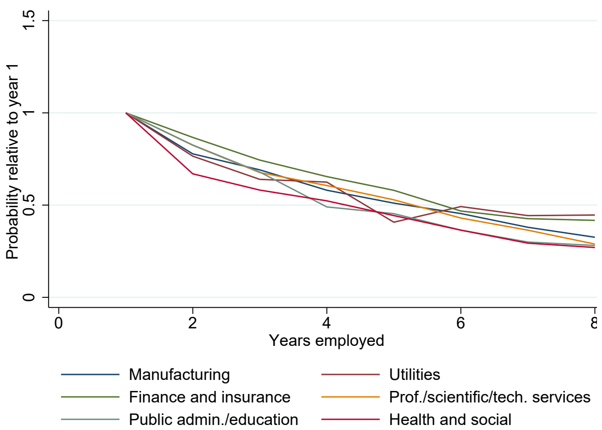
(a) High Non-Wage Industries, absolute



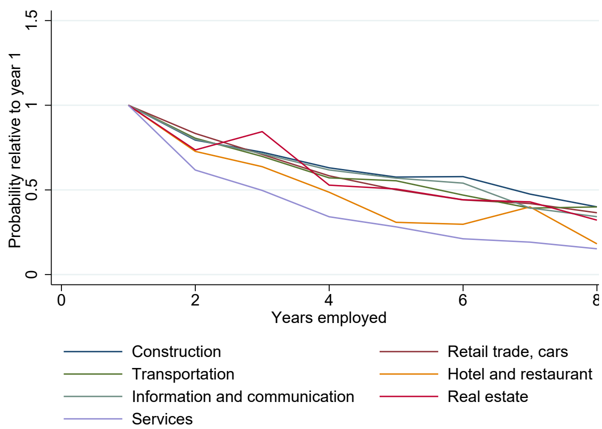
(b) Low Non-Wage Industries, absolute



(c) High Non-Wage Industries, relative



(d) Low Non-Wage Industries, relative



Notes: These figures plot the annual probability a worker in a given industry makes an employer-to-employer transition satisfying the criteria defined in Section 2. Figures a and b show the absolute probabilities, and figures c and d show the probabilities relative to the first year of tenure. Figures a and c show the six industries where firms on average offer the highest non-wage value, and figures b and d show the seven industries where firms in average offer the lowest non-wage value.

B Identification of Employer-Level Dynamics

While the following exposition follows Fink et al. (2010) with some adjustment tailored to my aim to identify all employer-level dynamics that do not follow a worker's binary choice.

I start by creating a quarterly panel of person-employer employment. I then identify the following employer level dynamics by applying the following criteria:

Rename: I classify an employer rename from A to B if

- Employer-identifier A exists in quarter t but not in quarter $t+1$
- Employer-identifier B does not exist in quarter t and exists in quarter $t+1$
- At least two third of individuals employed at employer A in quarter t are employed at employer B in quarter $t+1$
- Employer A has at least 3 employees in quarter t

Takeover: I classify an employer takeover from A to B if

- Employer-identifier A exists in quarter t but not in quarter $t+1$
- Employer-identifier B exists in quarter t and exists in quarter $t+1$
- At least two third of individuals employed at employer A in quarter t are employed at employer B in quarter $t+1$
- Employer A has at least 3 employees in quater t

Spin-off: I classify an employer spin-off from A to B if

- Employer-identifier A exists in quarter t and exists in quarter $t+1$
- Employer-identifier B does not exist in quarter t and exists in quarter $t+1$
- At least 10 percent of employees and at least three employees working at employer A in quarter t work at employer B in quarter $t+1$

Closure: I classify an employer closure of employer A if

- Employer-identifier A exists in quarter t but not in quarter $t+1$
- there is no rename or takeover

I merge employer-identifiers in case of a rename. If there is a takeover of employer A by employer B in quarter t I drop all transitions between employer A and employer B in quarter t and $t-1$. If there is a spin-off from employer A to employer B in quarter t I drop all transitions between employer A and employer B in quarter t and $t+1$. If there is an employer closure at employer A in quarter t I drop all transitions away from employer A in quarter t and $t-1$.[64] Table A.2 shows the number of transitions caused by the respective employer-level dynamics.

[64] By including adjacent quarters I account for the fact that employer-level transitions might not affect all workers at the exactly same point in time.

C Tables and Figures for 1996–2003 for Section 2 and Section 3.3

Table A.16: BY INDUSTRY – NUMBER OF HIRES AND QUITS
1996 – 2003

	Unweighted		Layoff weighted	
	Hires (1)	Quits (2)	Hires (3)	Quits (4)
Manufacturing	17,031	16,293	8,366	7,958
Utilities	1,201	919	444	300
Construction	4,762	4,207	1,563	1,629
Retail trade, cars	6,446	7,006	3,076	3,276
Transportation	3,774	4,029	1,846	2,094
Hotel and restaurant	299	309	122	154
Information and communication	3,494	2,523	1,824	1,454
Finance and insurance	6,042	6,141	2,470	2,424
Real estate	1,512	1,631	672	786
Prof./scientific/tech. services	3,651	4,460	1,587	1,766
Services	2,996	4,113	1,531	2,246
Public admin./education	5,204	4,152	2,538	2,027
Health and social	1,522	2,403	741	725

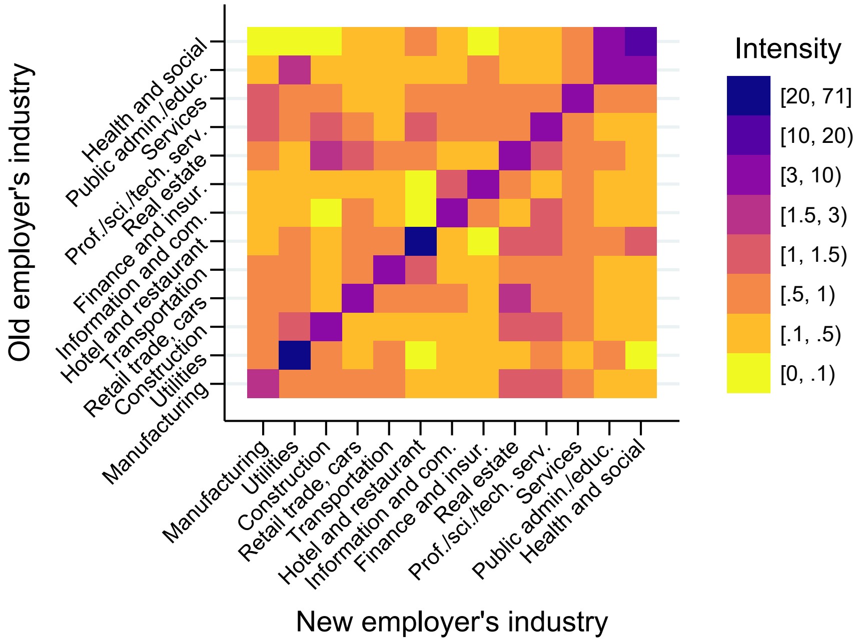
Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for the 1996–2003 sample. Columns 1 and 2: Number of hires and quits in sample by industry. Columns 3 and 4: Number of hires and quits by industry, after downweighting quits from contracting firms according to procedure explained in Section 2.

Figure A.6: EMPLOYMENT GROWTH AND TRANSITION PROBABILITIES 1996–2003

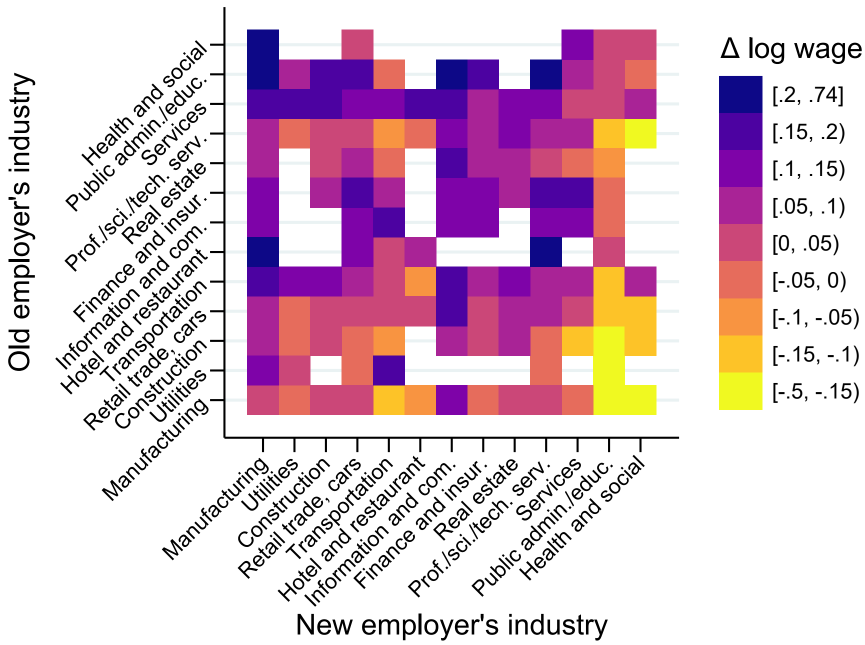
Notes: This figure shows the probability (per year) a worker in column 1 of Table 1 makes a transition, by 0.05 employer growth rate bin. Full-time employer-to-employer corresponds to the employer-to-employer transitions as defined in this section. Other employer-to-employer correspond to all transitions in which the worker starts at the new employer within 30 days, but do otherwise not satisfy the conditions detailed in this section. Employer-to-nonemployment are employment spells ending in year $t+1$ for which the worker does not join a new employer within 30 days. Share excess transitions as $\frac{\text{excess}}{\text{excess+expected}}$. Corresponding figure for 2004–2011 in Figure 2.

Figure A.7: EMPLOYER-TO-EMPLOYER TRANSITIONS AND WAGE DIFFERENTIALS 1996–2003

(a) Intensity of Employer-to-Employer Transitions



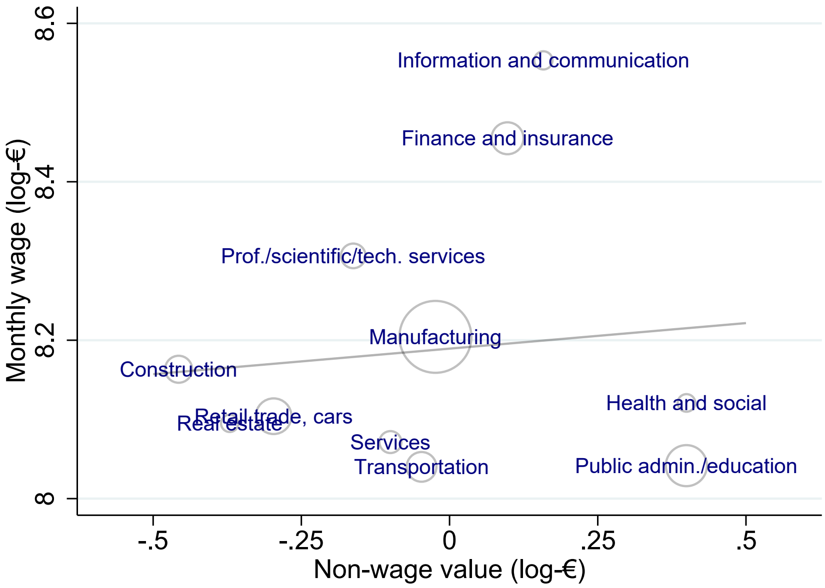
(b) Wage Differentials



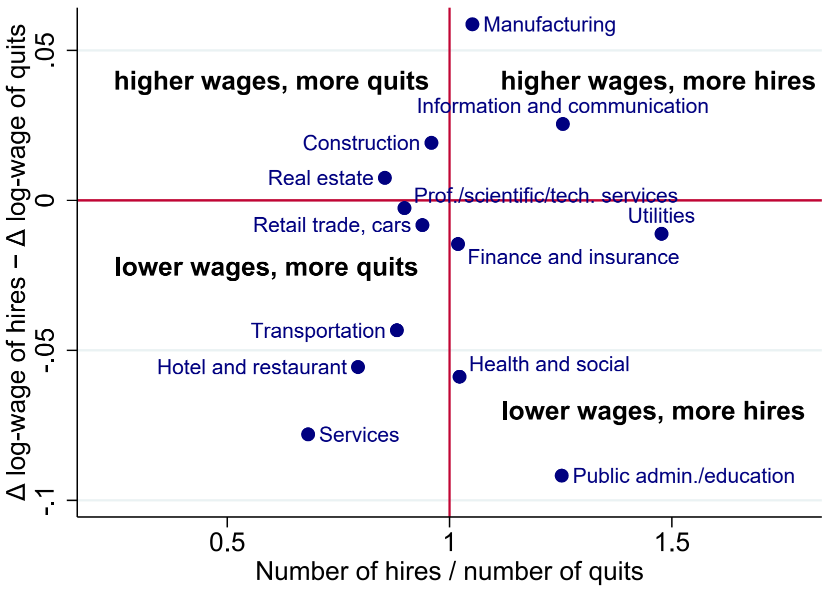
Notes: Figure a shows the intensity of employer-to-employer transitions between industries 1996–2003. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from the row-industry to the column-industry than expected under random mobility. See text in Section 2 for a formal definition of intensity. Figure b shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions with the old employer in the row-industry in the new employer in the column-industry. Missing cells in figure b contain fewer than 10 observations. Both figures are based on transitions between employers in the strongly connected 1996–2003 sample (column 2 of Table 1). See Figure A.10 for employer-to-employer transitions of all workers.

Figure A.8: HIRES, QUITS, WAGE DIFFERENTIALS AND NON-WAGE VALUES 1996–2003

(a) Non-Wage Values



(b) Employer-to-Employer Transitions and Wages



Notes: Figure a shows non-wage values and log-wages by industry, with circle size relative to the number of person-year observations in the corresponding industry. The gray line plots the regression line run at the industry level, with industries weighted by their number of person-year observations. Two industries are not shown in figure a: Utilities (coordinates: (.47,8.41)) and Hotel and restaurant (-.65,7.82). Figure b shows, on the x-axis, the number of employer-to-employer hires divided by the number of employer-to-employer quits (based on columns 3 and 4 of Table A.16), and on the y-axis: Log-wage increase of employer-to-employer hires minus log-wage increase of employer-to-employer quits (corrected for time/experience effects, based on Table A.5). Figures are based on the 1996–2003 sample (column 4 of Table 1). See Figure 4 for the 2004–2011 sample.

D Geralizability to Whole Austrian Labor Market

There are three restrictions I impose that distinct my sample from the whole population of workers in Austria, and that might raise concerns related to external validity:

1. My sample is limited to firms in the strongly connected set
2. My sample is limited to men
3. My sample is limited to full-time workers

In following, I will address 1.-3., showing that neither of the restrictions is likely to limit my sample in a way that affects external validity of my results with respect to the entire Austrian labor market.

D.1 Restriction 1: Only Strongly Connected Employers

In following I discuss descriptive statistics comparing the composition and dynamics in my sample of strongly connected employers (columns 2 and 4 of Table 1) with the composition and dynamics in the sample considering all employers (columns 1 and 3 of Table 1).

From Table 1 we see a comparison of my samples of strongly connected employers with all full-time working men. The largest differences are that men in my sample earn higher wages, and are more likely to work in manufacturing jobs. While these differences are substantial, two things are important to note. First, the difference in composition between my sample and all workers is about constant between 1996–2003 and 2004–2011. Second, dynamics of employer-to-employer transitions seem to be very similar in my sample as among all workers, as we can see from Panel D. of Table 1.

My estimator uses three pieces of information to identify non-wage values of firms: (1) the number of employer-to-employer hires of a firm compared to the number of employer-to-employer quits of a firm, (2) the pattern of these employer-to-employer hires and quits, and (3) the wage differentials associated with these employer-to-employer hires and quits. In following, I will thus compare descriptive statistics on the industry-level on (1)-(3) between all firms and my sample of strongly connected firms.

Tables A.17 and A.18 show the number of employer-to-employer hires and quits by industry in the Austrian labor market overall (columns 1 and 2) and in my sample (columns 3 and 4). Up to very few exceptions, industries where firms in my sample hire more workers than they loose workers are also industries that hire more workers than they loose workers if all firms are considered. Figures A.9 a & b and A.10 a & b show that also the pattern of worker flows between industries is similar in the Austrian labor market overall and in my sample of strongly connected firms.

Figures A.9 c & d and A.10 c & d and Tables A.19 and A.20 show wage differentials associated with employer-to-employer transitions. We see that disparities between my sample and all workers in terms of wage differentials are remarkably small.

The main result of this paper, that the inequality-attenuating effect of compensating differentials in the 1996–2003 panel was dominated by firm-level rents in the 2004–2011 panel, is driven by underlying changes in the pattern of worker flows and associated wage differentials. Figure A.3 shows how this pattern changed from 1996–2003 to 2004–2011 in my sample. Figure A.11 shows that this pattern changed in a very similar way in the Austrian labor market

Table A.17: BY INDUSTRY – NUMBER OF HIRES AND QUITS 1996 – 2003

	Overall		Strongly Connected	
	Hires	Quits	Hires	Quits
	(1)	(2)	(3)	(4)
Manufacturing	20,268	20,590	8,366	7,958
Utilities	1,372	860	444	300
Construction	6,006	7,417	1,563	1,629
Retail trade, cars	15,215	16,339	3,076	3,276
Transportation	6,042	6,357	1,846	2,094
Hotel and restaurant	1,414	1,890	122	154
Information and communication	4,203	3,372	1,824	1,454
Finance and insurance	4,903	4,671	2,470	2,424
Real estate	2,431	2,307	672	786
Prof./scientific/tech. services	5,198	5,754	1,587	1,766
Services	4,706	5,378	1,531	2,246
Public admin./education	6,886	4,118	2,538	2,027
Health and social	1,920	1,788	741	725

Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for 1996–2003. Columns 1 and 2: Number of hires and quits in Austrian labor market overall . Columns 3 and 4: Number of hires and quits by industry between firms in the sample of strongly connected firms. All statistics after downweighting quits from contracting firms according to procedure explained in Section 2.

overall, indicating that the result that compensating differentials in 1996–2003 got dominated by firm-level rents in 2004–2011 is not limited to my sample, but holds for the Austrian labor market overall.

Overall, the descriptive evidence let me conclude that the sample of strongly connected firms does not differ from the entire Austrian labor market in terms of structure and dynamics in a way that would substantially affect external validity of my results.

Table A.18: By Industry – Number of Hires and Quits 2004 – 2011

	Overall		Strongly Connected	
	Hires	Quits	Hires	Quits
	(1)	(2)	(3)	(4)
Manufacturing	23,015	21,175	12,659	10,256
Utilities	2,246	1,281	1,034	580
Construction	7,467	8,482	2,365	2,553
Retail trade, cars	15,987	16,339	4,193	4,425
Transportation	7,027	7,219	3,049	3,120
Hotel and restaurant	1,529	1,974	137	178
Information and communication	4,407	4,298	2,106	2,083
Finance and insurance	5,449	4,864	3,050	2,739
Real estate	2,091	2,004	601	686
Prof./scientific/tech. services	6,771	6,625	2,529	2,220
Services	6,304	11,035	2,600	6,434
Public admin./education	7,997	5,370	4,025	3,140
Health and social	2,050	1,894	840	806

Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for 2004–2011. Columns 1 and 2: Number of hires and quits in Austrian labor market overall . Columns 3 and 4: Number of hires and quits by industry between firms in the sample of strongly connected firms. All statistics after downweighting quits from contracting firms according to procedure explained in Section 2.

Figure A.9: EMPLOYER-TO-EMPLOYER TRANSITIONS AND WAGE DIFFERENTIALS 1996–2003

Notes: Figure a shows the intensity of employer-to-employer transitions between all firms. Figure b shows the intensity of employer-to-employer transitions between firms in the strongly connected sample. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from row-industry to column-industry than expected under random mobility. See text in Section 2 for formal definition of intensity. Figure c shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between all firms with old employer in industry in row and new employer in industry in column. Figure d shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between firms in the strongly connected sample with old employer in industry in row and new employer in industry in column. Missing cells in figures c and d contain fewer than 10 observations. These statistics are based on employer-to-employer transitions described in Table 1 (Figure a and c: Column 1; Figure b and d: Column 2).

Figure A.10: Employer-to-Employer Transitions and Wage Differentials 2004–2011

Notes: Figure a shows the intensity of employer-to-employer transitions between all firms. Figure b shows the intensity of employer-to-employer transitions between firms in the strongly connected sample. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from row-industry to column-industry than expected under random mobility. See text in Section 2 for formal definition of intensity. Figure c shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between all firms with old employer in industry in row and new employer in industry in column. Figure d shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between firms in the strongly connected sample with old employer in industry in row and new employer in industry in column. Missing cells in figures c and d contain fewer than 10 observations. These statistics are based on employer-to-employer transitions described in Table 1 (Figure a and c: Column 1; Figure b and 2: Column 2).

Table A.19: BY INDUSTRY – WAGES AND WAGE DIFFERENTIALS 1996 – 2003

	All (1)		Strongly connected (2)	
Median monthly wages by industry (2012 €)				
Manufacturing	3,365		3,674	
Utilities	3,432		4,023	
Construction	3,083		3,532	
Retail trade, cars	3,122		3,369	
Transportation	2,728		2,896	
Hotel and restaurant	2,187		2,414	
Information and communication	4,914		5,302	
Finance and insurance	4,506		4,855	
Real estate	3,233		3,516	
Prof./scientific/tech. services	3,783		3,972	
Services	2,909		3,015	
Public admin./education	2,780		2,972	
Health and social	2,927		3,004	
Δ *log-wage of employer-to-employer transitions*				
	Hires	Quits	Hires	Quits
Manufacturing	0.086	0.010	0.074	0.015
Utilities	0.011	0.022	0.014	0.026
Construction	0.037	0.015	0.025	0.006
Retail trade, cars	0.053	0.062	0.052	0.060
Transportation	0.004	0.044	0.019	0.062
Hotel and restaurant	-0.014	0.084	0.031	0.086
Information and communication	0.121	0.106	0.144	0.118
Finance and insurance	0.089	0.081	0.089	0.103
Real estate	0.048	0.027	0.038	0.030
Prof./scientific/tech. services	0.066	0.094	0.062	0.064
Services	0.041	0.097	0.031	0.109
Public admin./education	-0.037	0.086	-0.015	0.076
Health and social	0.014	0.080	-0.003	0.056

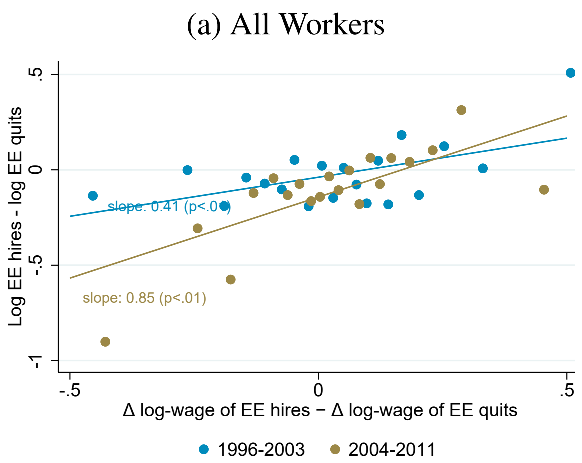
Note: This table reports wages and wage differentials by industry. Column 1 considers all workers according to column 1 of Table 1. Column 2 restricts the sample to workers at employers strongly connected by employer-to-employer transitions (column 2 in Table 1). The panel Δ *log-wage of employer-to-employer transitions* takes into account that wages at the old employer are observed in year t, and at the new employer in year $t+2$ by subtracting time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2). In the lower panel, transitions are weighted by their probability of being an excess separation as defined in the text in Section 2.

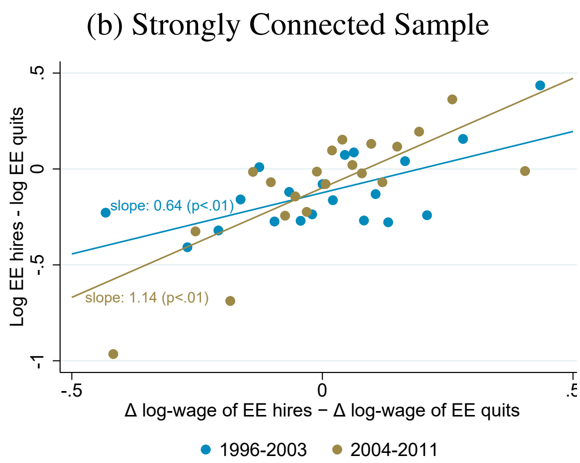
Table A.20: BY INDUSTRY – WAGES AND WAGE DIFFERENTIALS 2004 – 2011

	All		Strongly connected	
	(1)		(2)	
Median monthly wages by industry (2012 €)				
Manufacturing	3,569		3,781	
Utilities	4,103		5,294	
Construction	3,194		3,768	
Retail trade, cars	3,262		3,463	
Transportation	2,837		3,078	
Hotel and restaurant	2,240		2,455	
Information and communication	4,561		4,728	
Finance and insurance	4,900		5,188	
Real estate	3,450		3,405	
Prof./scientific/tech. services	4,244		4,586	
Services	2,938		3,004	
Public admin./education	3,081		3,516	
Health and social	3,163		3,493	
Δ log-wage of employer-to-employer transitions				
	Hires	Quits	Hires	Quits
Manufacturing	0.069	0.005	0.061	0.004
Utilities	0.035	0.029	0.042	0.040
Construction	0.054	0.021	0.056	0.013
Retail trade, cars	0.054	0.058	0.057	0.060
Transportation	0.023	0.045	0.034	0.048
Hotel and restaurant	-0.011	0.079	-0.025	0.070
Information and communication	0.059	0.048	0.054	0.046
Finance and insurance	0.075	0.072	0.083	0.090
Real estate	0.055	0.049	0.042	0.035
Prof./scientific/tech. services	0.069	0.086	0.073	0.078
Services	0.031	0.078	0.018	0.078
Public admin./education	-0.020	0.083	-0.002	0.092
Health and social	0.010	0.055	-0.005	0.048

Note: This table reports wages and wage differentials by industry. Column 1 considers all workers according to column 3 of Table 1. Column 2 restricts the sample to workers at employers strongly connected by employer-to-employer transitions (column 4 of Table 1). The panel Δ *log-wage of employer-to-employer transitions* takes into account that wages at the old employer are observed in year t, and at the new employer in year $t + 2$ by subtracting time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2). In the lower panel, transitions are weighted by their probability of being an excess separation as defined in the text in Section 2.

Figure A.11: Descriptive Evidence on Relationship Between Employer Attractiveness and Employer Wage Premium from 1996–2003 to 2004–2011





Notes: These figures show the relationship between the log of $\frac{\text{employer-to-employer hires}}{\text{employer-to-employer quits}}$ and the log of $\frac{\text{average wage increase of employer-to-employer hires}}{\text{average wage increase of employer-to-employer quits}}$. Firms for 1996–2003 (Figure a: Column 1 of Table 1; Figure b: Column 2 of Table 1) and 2004–2011 (Figure a: Column 3 of Table 1; Figure b: Column 4 of Table 1) separately grouped into 20 firm-size (measured by the number of people-years) weighted bins, grouped by the x-axis variable. The regression lines represent the slope of an OLS regression, with firms weighted by the number of person-year observations they represent in the corresponding sample period.

D.2 Restriction 2: Only Male Workers

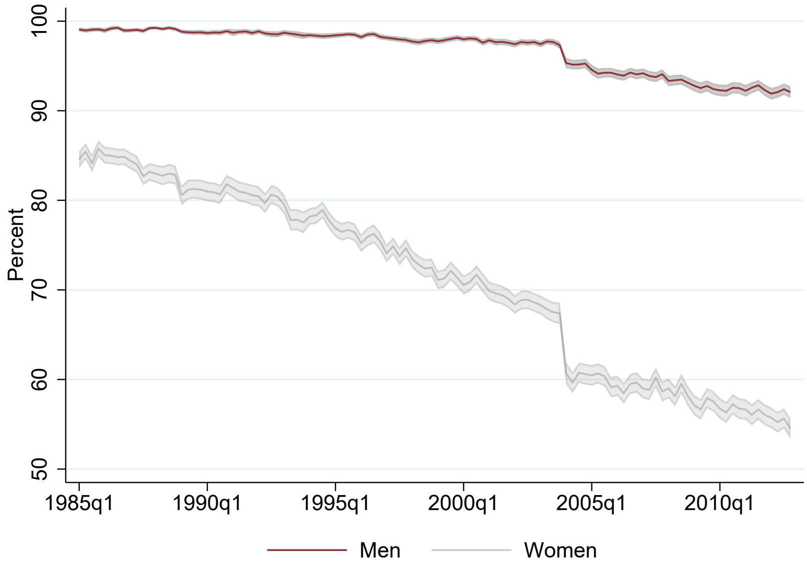
I restrict my sample to male workers because a large share of female workers are working part-time (Figure A.12), and I can only identify part-time workers after 2002 in my data. Thus, while I cannot make any statement on full-time working women in the 1996–2003 panel, I can compare my sample for 2004–2011 with the sample that obtains if full-time working women are included, which I will do in following.

Table A.21 compares my sample of workers in 2004–2011 with the sample including full-time working women. Differences arise in that women earn less than men, and that women are more likely to work in traditional female-dominated industries such as public administration/education and health and social services.

Panel D. of Table A.26 shows that regarding transitions and associated wage differentials my baseline sample (column 4) looks similar to the sample including full-time working women (column 2). This is also confirmed when comparing industry-level descriptive statistics on the number of hires and quits (Table A.22), the pattern of transitions (Figure A.13), and the wage differentials associated with employer-to-employer transitions (Table A.23).

I estimate the model described in Section 3 using employer-to-employer transitions of women (column 2 of Table A.21), and conduct the same job value variance decomposition as I do for the baseline sample (Table A.24). I find a close to 10 percent greater overall variance of job value when estimating the sample with women (Table A.25). This is driven by greater estimates of firm non-wage value dispersion, and dispersion of idiosyncratic non-wage value. I find, however, very similar values regarding my two main results: (1) a very similar positive covariance of non-wage value and wage (4th and 5th row of Table A.25); (2) a positive covariance between firm wage and firm non-wage value offer (6th row of Table A.25), confirming the result of dominating firm-level rents in 2004–2011.

Figure A.12: SHARE MEN AND WOMEN EMPLOYED FULL-TIME 1995–2012



Notes: This figure shows the evolution of the share of all workers in dependent employment that is working full-time separately for men and women. It is based on data from the Austrian Mikrozensus (Austrian labor force survey). I classify a worker as full-time employed if he reports working at least 36 hours in a normal work week. The discontinuity in year 2004 is due to a reform of the Mikrozensus, including change in definition of employment status, that was implemented in that year (Lehmann, 2019).

Table A.21: POPULATION AND SAMPLE 2004–2011 WITH AND WITHOUT WOMEN

	With Women		Men Only	
	All (1)	**Strongly connected** (2)	**All** (3)	**Strongly connected** (4)
A. Sample size				
People-years	15,488,900	8,133,160	9,906,446	5,480,901
People	2,927,762	1,534,497	1,712,585	964,635
Employers	260,429	5,944	182,811	5,944
B. Summary Statistics				
Share Female	0.36	0.33	0.00	0.00
Mean age	39.81	39.78	40.21	40.21
Share blue collar	0.35	0.32	0.43	0.39
Median monthly wage (2012 €)	2,948	3,253	3,196	3,481
Mean log monthly wage	8.03	8.15	8.14	8.23
Mean log monthly wage	8.03	8.15	8.14	8.23
Var log monthly wage	0.22	0.20	0.21	0.20
C. Industry Shares				
Manufacturing	0.25	0.31	0.31	0.39
Utilities	0.02	0.02	0.02	0.03
Construction	0.07	0.04	0.10	0.06
Retail trade, cars	0.16	0.11	0.15	0.10
Transportation	0.06	0.07	0.07	0.08
Hotel and restaurant	0.03	0.01	0.02	0.00
Information and communication	0.03	0.03	0.03	0.03
Finance and insurance	0.05	0.07	0.05	0.06
Real estate	0.02	0.01	0.02	0.02
Prof./scientific/tech. services	0.05	0.03	0.04	0.03
Services	0.06	0.05	0.05	0.05
Public admin./education	0.15	0.20	0.10	0.13
Health and social	0.05	0.04	0.02	0.02
D. Employer-to-employer transitions				
Transitions	265,904	100,529	178,835	74,271
Share excess separations	0.47	0.45	0.48	0.47
Mean log wage increase	0.10	0.10	0.09	0.10
Mean log wage increase (adjusted)†	0.05	0.05	0.05	0.05
Share wage increase (adj.)	0.59	0.60	0.59	0.60
Share both employers same industry	0.44	0.46	0.43	0.45

Note: Summary statistics on the sample of full-time workers 2004–2011, when restricting the sample to male workers (columns 3 and 4), and without any restriction on workers' sex (columns 1 and 2). Columns 3 and 4 correspond to columns 3 and 4 of Table 1. The industry classification is based on NACE Rev. 2 main sections. I combined section D & E (Utilities), O & P (Public admin./education) and N & S (Services). Not shown: Agriculture, forestry and fishing, Mining, Arts and entertain., Households as employers, (All share people-years in 1996–2003 <0.01). All summary statistics on transitions (Panel D. after *Share excess separations*) are with observations weighted by their probability of being an excess separation as defined in the text.

† The wage at the old employer is observed in year t, and the wage at the new employer in year $t+2$. I substract time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2)

Table A.22: BY INDUSTRY – NUMBER OF HIRES AND QUITS 2004–2011, WITH AND WITHOUT WOMEN

	With Women		Men Only	
	Hires (1)	Quits (2)	Hires (3)	Quits (4)
Manufacturing	15,015	12,029	12,659	10,256
Utilities	1,202	686	1,034	580
Construction	2,557	2,708	2,365	2,553
Retail trade, cars	6,188	6,641	4,193	4,425
Transportation	3,774	4,053	3,049	3,120
Hotel and restaurant	237	309	137	178
Information and communication	2,660	2,689	2,106	2,083
Finance and insurance	4,993	4,670	3,050	2,739
Real estate	834	907	601	686
Prof./scientific/tech. services	3,476	3,129	2,529	2,220
Services	3,701	8,238	2,600	6,434
Public admin./education	8,475	7,150	4,025	3,140
Health and social	2,175	2,126	840	806

Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for 2004–2011. Columns 1 and 2: Number of hires and quits in sample without any restriction on workers' sex (column 2 Table A.21). Columns 3 and 4: Number of hires and quits in baseline sample of men (column 4 Table A.21). All statistics after downweighting quits from contracting firms according to procedure explained in Section 2.

Table A.23: By Industry – Wages and Wage Differentials 2004–2011 With and Without Women

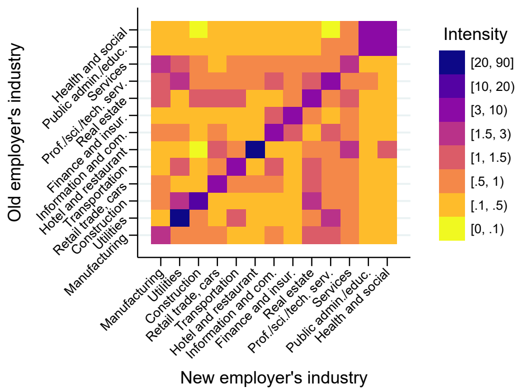
	With Women		**Men Only**	
	(1)		(2)	
Median monthly wages by industry (2012 €)				
Manufacturing	3,426		3,582	
Utilities	4,700		4,852	
Construction	3,325		3,342	
Retail trade, cars	2,755		3,039	
Transportation	2,857		2,932	
Hotel and restaurant	2,089		2,236	
Information and communiaction	4,725		5,017	
Finance and insurance	4,435		5,054	
Real estate	3,028		3,185	
Prof./scientific/tech. services	3,857		4,211	
Services	2,668		2,826	
Public admin./education	3,073		3,248	
Health and social	3,009		3,211	
Δ *log-wage of employer-to-employer transitions*	Hires	Quits	Hires	Quits
Manufacturing	0.062	0.006	0.061	0.004
Utilities	0.047	0.041	0.042	0.040
Construction	0.056	0.014	0.056	0.013
Retail trade, cars	0.057	0.058	0.057	0.060
Transportation	0.036	0.047	0.034	0.048
Hotel and restaurant	-0.008	0.079	-0.025	0.070
Information and communiaction	0.058	0.045	0.054	0.046
Finance and insurance	0.080	0.075	0.083	0.090
Real estate	0.043	0.043	0.042	0.035
Prof./scientific/tech. services	0.073	0.078	0.073	0.078
Services	0.020	0.079	0.018	0.078
Public admin./education	0.022	0.069	-0.002	0.092
Health and social	-0.007	0.024	-0.005	0.048

Note: This table reports wages and wage differentials by industry, using the samples of strongly connected firms (columns 2 and 4 of Table A.21). The panel Δ *log-wage of employer-to-employer transitions* takes into account that wages at the old employer are observed in year t, and at the new employer in year $t + 2$ by subtracting time and experience effects from the wage at the new employer using the estimates from my AKM-regression (see Appendix G.2). In the lower panel, transitions are weighted by their probability of being an excess separation as defined in the text in Section 2.

Figure A.13: Employer-to-Employer Transitions and Wage Differentials 2004–2011, Sample With Women and Men Only

Intensity of Employer-to-Employer Transitions

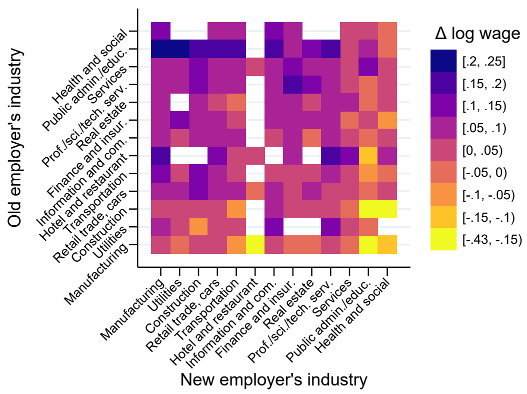
(a) With Women



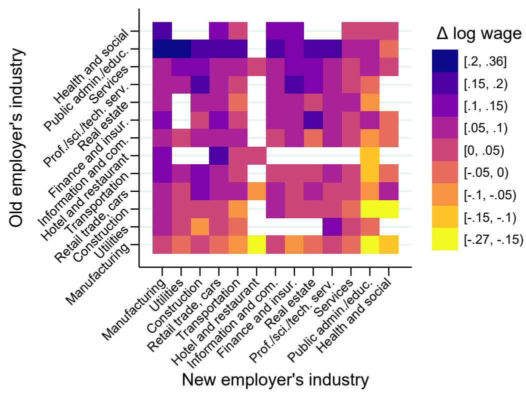
(b) Men Only

Wage Differentials

(c) With Women



(d) Men Only



Notes: Figure a shows the intensity of employer-to-employer transitions between firms in the strongly connected sample using all full-time workers. Figure b shows the intensity of employer-to-employer transitions between firms in the strongly connected sample using male full-time workers only. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from row-industry to column-industry than expected under random mobility. See text in Section 2 for formal definition of intensity. Figure c shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between firms in the strongly connected sample using all full-time workers with old employer in industry in row and new employer in industry in column. Figure d shows average log-wage differences (new log-wage − old log-wage) of employer-to-employer transitions between firms in the strongly connected sample using male full-time workers only with old employer in industry in row and new employer in industry in column. Missing cells in figures c and d contain fewer than 10 observations. These statistics are based on employer-to-employer transitions shown in Table A.21 (Figure a and c: Column 2; Figure b and d: Column 4).

Table A.24: Covariances of Job Value Components – Sample With Women

		Job value	Wage	Non-wage	Wage				Non-wage	
					Person	Employer	$\boldsymbol{X}'_{it}\beta$	r_{it}	Employer	Idio.
	Job value	0.616								
	Wage	0.238	0.190							
	Non-wage	0.378	0.048	0.330						
Wage	Person	0.198	0.157	0.040	0.154					
Wage	Employer	0.024	0.019	0.006	0.006	0.013				
Wage	$\boldsymbol{X}'_{it}\beta$	0.002	0.001	0.001	-0.003	-0.001	0.005			
Wage	r_{it}	0.014	0.014	0	0	0	0	0.014		
Non-wage	Employer	0.270	0.048	0.223	0.040	0.006	0.001	0	0.223	
Non-wage	Idiosyncratic	0.107	0	0.107	0	0	0	0	0	0.107

Notes: This table reports covariances of job-value components in the sample of all full-time workers. The covariances are estimated using all person-year observations from Table A.21 column 2. The corresponding covariance matrix for the sample using male full-time workers only is in Table A.8.

Table A.25: Job Value Variance 2004–2011, With Women and Without Women

	With Women (1)	Men Only (2)
$Var(V_{ij})$	0.616	0.564
$Var(ln(w_{ij}))$	0.190	0.197
$Var(a_j + \epsilon_{ij})$	0.330	0.277
$2Cov(w_{ij}, a_j + \epsilon_{ij})$	0.095	0.090
$2Cov(\alpha_i, a_j)$	0.081	0.082
$2Cov(\psi_j, a_j)$	0.012	0.006

Notes: This table reports the variance of job value and covariances of components of job value 2004–2011, in column 1 in the sample of all full-time workers (Table A.21 column 2), and in column 2 in the sample of male full-time workers only (Table A.21 column 4).

D.3 Restriction 3: Only Full-Time Workers

In order to give earnings recorded in administrative data the interpretation of a piece-rate wage, I limit my sample to full-time workers.[65] While I lack information on wages of part-time workers, I can compare the composition of my sample with the sample including part-time workers, and the employer-to-employer transition dynamics in the two samples, which I will do in following.

Table A.26 compares the sample of full-time male workers (columns 2 and 4) with the sample that obtains if women and part-time workers are included (columns 1 and 3). We see that this increases the sample size by more than 50 percent, as well as the number of employer-to-employer transitions (Panel D.).

Table A.27 and Figure A.14 show that patterns of worker flows, when aggregated at the industry level, look very similar in my sample and when including part-time workers and women. This suggests that, indeed, preferences over firms are similiar among all workers as in my sample.[66]

I can estimate firm value offers in the framework of my search model by replacing $ln(w)+a$ by U, which then allows me to directly estimate each employer's total value offer solely using worker flows.[67] Hence, I estimate two U using the likelihood function in Proposition 1, one relying on employer-to-employer transitions of full-time workers in my sample only, and one including employer-to-employer transitions of part-time workers. I otherwise apply the same restrictions for part-time workers' employer-to-employer transitions (see Section 2).

Table A.29 shows model parameters from estimating the model on the two samples for the 1996–2003 and the 2004–2011 period. We see that including part-time workers and women increases the number of transitions between firms by more than 50 percent, and that the firm size parameter and the number of hires from non-employment are about 100 percent greater. Nevertheless, I find that the employer values estimated on the two samples are .9-correlated. This high correlation of total firm value offers suggests that preferences of part-time workers and full-time workers are highly correlated, especially if we consider that sampling variation biases the correlation downwards. I therefore conclude that part-time workers and full-time workers are likely offered similar non-wage values by the employers in my sample.

Sorting of Workers in Sample Vs. Whole Austrian Labor Market Industries explain 31 percent (1996–2003, 25 percent 2004–2011) of the variance of employers' non-wage value.[68] Comparing the distribution of all Austrian workers across industries with the distribution of workers across industries in my sample will thus help understand the extent to which my results are valid for the whole Austrian labor market. Figure A.15 shows how workers in Austria are sorted across industries. The industries in Figure A.15 are ordered by their employers' average non-wage value. Comparing the sorting of workers in my sample to the sorting of workers

[65] Recall that I can identify full-time workers after 2002, and use before 2002 that more than 97 percent of men are working full-time.

[66] This holds if employers offer similar wage premia to part-time workers as to full-time workers.

[67] I can also calculate the average value an employer offers to its employed workers by using the formula $U^{employed} = \psi + a$. Reassuringly, I obtain a correlation of .98 between the directly estimated total value offer and $U^{employed}$ (that the correlation is slightly lower than 1 might be explained by the difference between the offered wage premium ψ and the wage premium workers employed at an employer actually have.)

[68] This is the R^2 of a regression of employers' non-wage value on industry dummies, weighting employers by their number of person-year observations.

Table A.26: STONGLY CONNECTED FIRMS INCLUDING/EXCLUDING PART-TIME WORKERS AND WOMEN 1996–2003 & 2004–2011

	1996 – 2003		**2004–2011**	
	All	**Full-Time Men**	**All**	**Full-Time Men**
	(1)	(2)	(3)	(4)
A. Sample size				
People-years	7,833,859	4,513,833	9,913,346	5,480,901
People	1,413,665	797,492	1,775,902	964,635
Employers	4,544	4,544	5,944	5,944
B. Summary Statistics				
Mean age	38.70	39.07	40.13	40.21
Share blue collar	0.33	0.43	0.28	0.39
Share female	0.40	0.00	0.41	0.00
Share full-time			0.84	1.00
C. Industry Shares				
Manufacturing	0.29	0.39	0.28	0.39
Utilities	0.02	0.03	0.02	0.03
Construction	0.04	0.05	0.04	0.06
Retail trade, cars	0.11	0.10	0.12	0.10
Transportation	0.06	0.07	0.06	0.08
Hotel and restaurant	0.01	0.00	0.00	0.00
Information and communication	0.02	0.02	0.03	0.03
Finance and insurance	0.08	0.08	0.07	0.06
Real estate	0.02	0.02	0.01	0.02
Prof./scientific/tech. services	0.04	0.05	0.03	0.03
Services	0.05	0.04	0.05	0.05
Public admin./education	0.22	0.13	0.22	0.13
Health and social	0.05	0.02	0.06	0.02
D. Employer-to-employer transitions				
Transitions	92,902	58,349	117,855	74,271
Share excess separations	0.52	0.54	0.43	0.47
Share both employers same industry	0.48	0.47	0.46	0.45

Note: This table reports summary statistics on all workers working at least one full calendar year at strongly connected firms (columns 1 and 3) and those satisfying the baseline sample restrictions (columns 2 and 4). Information on full-time/part-time employment only available for 2004–2011 panel. The industry classification is based on NACE Rev. 2 main sections. I combined section D & E (Utilities), O & P (Public admin./education) and N & S (Services). Not shown: Agriculture, forestry and fishing, Mining, Arts and entertain., Households as employers, (All share people-years in 1996–2003 <0.01). All summary statistics on transitions (Panel D. after *Share excess separations*) are with observations weighted by their probability of being an excess separation as defined in the text.

in the entire Austrian labor market, we see that my sample has a lower share of workers in industries at the lower end of the non-wage value distribution, while workers in my sample

Table A.27: BY INDUSTRY – NUMBER OF HIRES AND QUITS 1996–2004, INCLUDING/EXCLUDING PART-TIME WORKERS AND WOMEN

	All		Full-time Men	
	Hires (1)	Quits (2)	Hires (3)	Quits (4)
Manufacturing	11,119	10,159	8,366	7,958
Utilities	594	394	444	300
Construction	1,802	1,852	1,563	1,629
Retail trade, cars	5,334	6,030	3,076	3,276
Transportation	2,703	3,052	1,846	2,094
Hotel and restaurant	252	347	122	154
Information and communication	2,757	2,302	1,824	1,454
Finance and insurance	4,497	4,385	2,470	2,424
Real estate	968	1,101	672	786
Prof./scientific/tech. services	2,328	2,522	1,587	1,766
Services	2,721	3,864	1,531	2,246
Public admin./education	6,479	5,842	2,538	2,027
Health and social	2,681	2,530	741	725

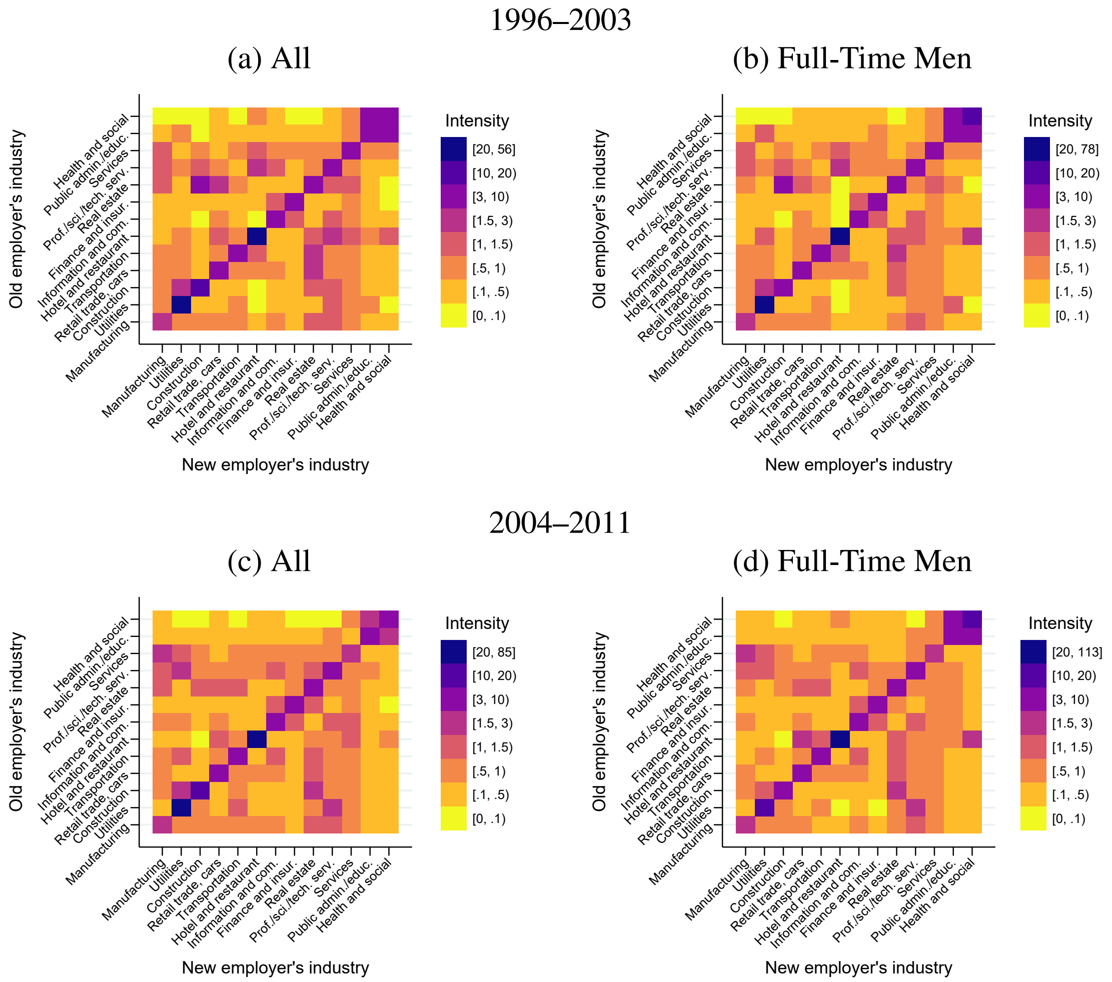
Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for 1996–2003. Columns 1 and 2 show the number of hires and quits in sample with part-time workers and women (column 1 of Table A.26). . Columns 3 and 4 show the number of hires and quits in baseline sample (column 2 of Table A.26). All statistics after downweighting quits from contracting firms according to procedure explained in Section 2.

Table A.28: BY INDUSTRY – NUMBER OF HIRES AND QUITS 2004–2012, INCLUDING/EXCLUDING PART-TIME WORKERS AND WOMEN

	All		Full-time Men	
	Hires	Quits	Hires	Quits
	(1)	(2)	(3)	(4)
Manufacturing	16,826	13,165	12,659	10,256
Utilities	1,355	774	1,034	580
Construction	2,767	2,970	2,365	2,553
Retail trade, cars	7,695	8,575	4,193	4,425
Transportation	4,288	4,507	3,049	3,120
Hotel and restaurant	277	383	137	178
Information and communication	3,049	3,163	2,106	2,083
Finance and insurance	5,829	5,454	3,050	2,739
Real estate	951	1,013	601	686
Prof./scientific/tech. services	4,045	3,586	2,529	2,220
Services	4,881	10,281	2,600	6,434
Public admin./education	11,611	9,727	4,025	3,140
Health and social	3,548	3,575	840	806

Note: This table reports totals of employer-to-employer hires and employer-to-employer quits by industry for 2004–2011. Columns 1 and 2 show the number of hires and quits in sample with part-time workers and women (column 3 of Table A.26). . Columns 3 and 4 show the number of hires and quits in baseline sample (column 4 of Table A.26). All statistics after downweighting quits from contracting firms according to procedure explained in Section 2.

Figure A.14: INTENSITY OF EMPLOYER-TO-EMPLOYER TRANSITIONS, INCLUDING/EXCLUDING PART-TIME WORKERS AND WOMEN



Notes: Figure a and c show the intensity of employer-to-employer transitions between firms in the strongly connected sample using all workers. Figure b and d show the intensity of employer-to-employer transitions between firms in the strongly connected sample using male full-time workers only. If mobility was random, the intensity would be equal to 1 for each cell. Intensities above 1 indicates that there are more transitions from row-industry to column-industry than expected under random mobility. See text in Section 2 for formal definition of intensity. Based on employer-to-employer transitions shown in Table A.26 (Figure a: Column 1 Table A.26; Figure b: Column 2 Table A.26; Figure c: Column 3 Table A.26; Figure d: Column 4 Table A.26).

are more strongly sorted to employers at the upper end of the non-wage value distribution.[69] This industry level statistics suggests that while the average non-wage value in my sample is higher than in the Austrian labor market overall, the dispersion of non-wage values is probably similar. Indeed, on the industry level, the variance of non-wage value is only slightly lower when weighting the industries by the number of person-year observations in my sample (var $= .051$ in 1996–2003 and 2004–2011), than when using full-time workers (var $= .054$ in 1996–2003 and var $= .055$ in 2004–2011), or all workers (var $= .058$ in 1996–2003 and var $= .059$

[69]This difference is probably explained by employer size and employment duration, which is both substantially higher for employers in the manufacturing or public administration/education industries than for employers in the hotel and restaurant, services, or retail trade and cars industries.

Table A.29: Total Firm Value Offers, Including/Excluding Part-Time Workers and Women

	1996 – 2003		2004–2011	
	All	**Full-Time Men**	**All**	**Full-Time Men**
	(1)	(2)	(3)	(4)
Model				
Transitions	92,902	58,349	117,855	74,271
Firm size (people-years)	1,376	799	1,310	727
Hires from non-employment	123	60	126	59
Correlation of firm value offers				
Corr. U all, U full-time men	0.90		0.90	

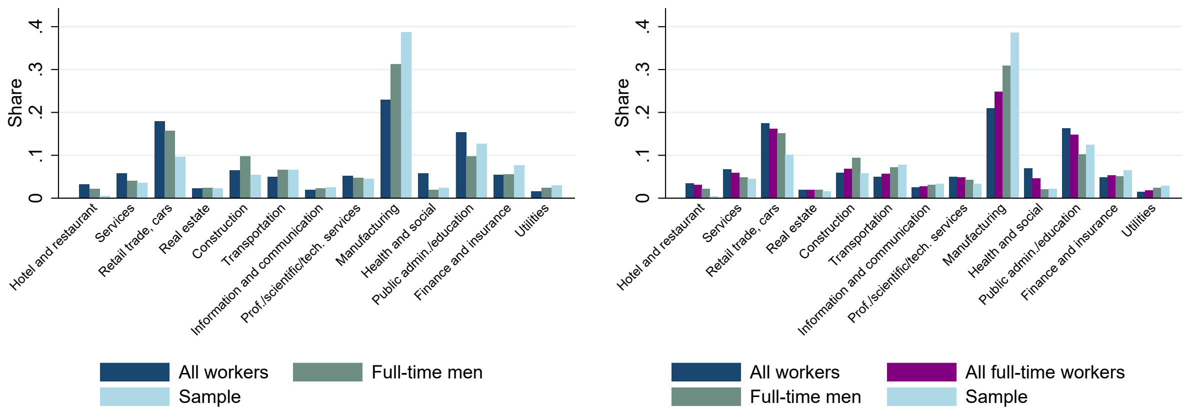
Notes: The panel *Model* of this table reports the number of employer-to-employer transitions and parameter values of the model estimated with all workers (columns 1 and 3 of Table A.26), and with full-time male workers only (columns 2 and 4 of Table A.26). The panel *Correlation of firm value offers* shows the correlation of employer values estimated with the two sets of transitions using the likelihood function in Proposition 1 with $U = ln(w) + ln(a)$, that is, $\mathcal{L} = \prod_{s=1}^{S} \Phi[U_j - U_k]^{\frac{1}{f_j^{NE}} \frac{1}{g_k}}$.

in 2004–2011).

Figure A.15: Sorting of Workers in Sample and in Austrian Labor Market

(a) 1996–2003 Panel

(b) 2004–2011 Panel



Notes: These figures show the share of person-year observations by industry for different subsamples for the 1996–2003 and the 2004–2011 panel. *All workers* denotes the sample containing all workers employed at a single employer for the full calendar year. *All full-time workers* denotes the sample containing all workers employed full-time at a single employer for the full calendar year (only available for 2004–2011). *Full-time men* denotes all male workers employed full-time at a single employer fo the full calendar year (columns 1 and 3 of Table 1). *Sample* denotes my baseline sample, which are all male workers employed full-time at a single employer that is in the strongly connected set for the full calendar year (columns 2 and 4 of Table 1).

Overall, I conclude that employers in my sample likely offer similar non-wage values to part-time workers as to full-time workers. I find no evidence that workers from the entire

Austrian labor market are sorted to employers in a way that would alter my conclusions on non-wage value dispersion and its implications for inequality.

E Derivation of the Model and Estimator in Section 3

E.1 Value Functions

Employed Workers Employed workers' value of being at employer k is characterized by the following Bellman equation:[70]

$$\underbrace{(\alpha_{it} + \tilde{\psi}_k) + ln(a_k)}_{\text{value of being at } k} = \underbrace{v(\alpha_{it}, \tilde{\psi}_k, a_k)}_{\text{flow payoff}}$$

$$+ \underbrace{\beta}_{\text{discounter}} \Bigg[\underbrace{\delta_k(1-\rho_k)V^n}_{\substack{\text{exogenous employer-}\\ \text{to-non-employment}}} + \underbrace{\delta_k\rho_k \sum_j \int_\eta \int_\epsilon ((\alpha_{it} + \tilde{\psi}_j + \eta_j) + ln(a_j) + \epsilon_j) dF(\eta) dF(\epsilon) f_{jk} +}_{\text{exogenous employer-to-employer}} \underbrace{(1-\delta_k)}_{\text{no exogenous transition}} *$$

$$\underbrace{\lambda_1 \sum_j \int_{\eta_1} \int_{\eta_2} \int_{\epsilon_1} \int_{\epsilon_2} \max\{(\alpha_{it} + \tilde{\psi}_k + \eta_k) + ln(a_k) + \epsilon_k, (\alpha_{it} + \tilde{\psi}_j + \eta_j) + ln(a_j) + \epsilon_j\} dF(\eta_1) dF(\eta_2) dF(\epsilon_1) dF(\epsilon_2) f_{jk}}_{\text{receive job offer and make binary choice}}$$

$$+ \underbrace{(1-\lambda_1)}_{\text{no job offer}} ((\alpha_{it} + \tilde{\psi}_k) + ln(a_k))) \Bigg] \tag{A.1}$$

meaning that a worker at employer k has value composed of its wage and non-wage value, which equals his flow payoff as well as a continuation value which is discounted by β. The part of the continuation value relevant for my estimation is the case when the worker receives a job offer and makes a binary choice, which happens with probability $(1-\delta_k)\lambda_1$. The intensity of offers from employer j is f_{jk}. When the worker receives an offer from an outside employer j, he draws a new offer from employer k, compares the two offers, and selects the one offering him greater value. This process is represented by the two terms in the max-function. There are two stochastic elements associated with the decision to choose the maximum: first, there is randomness in the wages the two employers offer η, and second, there is the workers' idiosyncratic valuation for each employer's offer ϵ.

Non-Employed Workers Non-employed workers' value is characterized by the following Bellman equation:

$$\underbrace{V^n}_{\text{value of non-empl.}} = b + \beta \left(\underbrace{\lambda_0 \sum_j \int_\eta \int_\epsilon ((\alpha_{it} + \tilde{\psi}_j + \eta_j) + ln(a_j) + \epsilon_j) dF(\eta) dF(\epsilon) f^{ne}_{ji}}_{\text{receive job offer}} + \underbrace{(1-\lambda_0)V^n}_{\text{no offer}} \right) \tag{A.2}$$

Where λ_0 represents the probability with which non-employed workers receive job offers and f^{NE}_{ji} represents worker i's probability of receiving an offer from employer j. Hence, non-employed workers probability of receiving a job offer from a particular employer is allowed to

[70] Following Arcidiacono and Ellickson (2011, p. 368) I write the value function as the value of being at employer k just before the first idiosyncratic draws ι and η are revealed, which is why the idiosyncratic draws do not show up in the flow utility.

depend on his characteristics (e.g., education, skills). In the case when non-employed workers receive an employment offer, they draw η and ϵ and accept the offer.

I assume that $\lambda_0 * \mathbb{E}_i[f_{ji}^{NE}] = \lambda_1 * \mathbb{E}_{ik}[f_{j,ik}]$, that is, that non-employed workers in expectation receive offers with the same relative intensity from a particular employer as employed workers. This allows me to estimate the intensity with which employers make offers to employed workers from where non-employed workers get hired.

E.2 Proof of Proposition 1

The idea of the proof is to show that in the limit (that is, when the number of periods in which firms make offers gets large) under my model's assumptions and correcting for employers' size and offer intensity, accepted job offers (leading to employer-to-employer transitions) made by employer j to workers at employer k are equivalent to rejected job offers (not leading to employer-to-employer transitions) made by employer k to workers at employer j, why the non-wage value of employer j is pairwise (over-)identified from employer-to-employer transitions with any other employer connected to employer j.

Start by noting that by equation A.1 the probability in a given time period that a worker at employer k who has not made an exogenous transition (either to non-employment or another employer) receives an offer from employer j equals $\lambda_1 f_{jk}$. With g_k workers at employer k who have no exogenous transition, over T time periods there is a sequence $(\lambda_1 f_{jk})_{s\,\in\, T*g_k}$ of offers from employer j of which $\sum_{s\,\in\, Tg_k} \lambda_1 f_{jk}\mathbb{1}(j>k)_s$ are accepted and $\sum_{s\,\in\, Tg_j} \lambda_1 f_{kj}\mathbb{1}(j<k)_s$ are rejected, where

$$\mathbb{1}(j>k)_s = \mathbb{1}((\tilde{\psi}_j + \eta_{js}) + ln(a_j) + \epsilon_{js} > (\tilde{\psi}_k + \eta_{ks}) + ln(a_k) + \epsilon_{ks})$$

by the assumption that $\epsilon \sim i.i.d.N(0,\sigma^2)$, we obtain that the expected number of workers per period at employer k receiving and <u>accepting</u> an offer from employer j is

$$\begin{aligned} \lim_{T\to\infty} \frac{1}{T}(\lambda_1 f_{jk}\mathbb{1}(j>k))_{s\,\in\, Tg_j} = \\ \lambda_1 g_k f_{jk} \int_{(\eta_j-\eta_k)} \Phi(((\tilde{\psi}_j - \tilde{\psi}_k) + (\eta_j - \eta_k)) + ln(a_j) - ln(a_k)) dF(\eta_j - \eta_k) \end{aligned} \tag{A.3}$$

where Φ denotes the cumulative distribution function of a normal distribution with mean zero and variance $2\sigma^2$. The expected number of workers per period at employer k receiving and <u>rejecting</u> an offer from employer j is

$$\lim_{T\to\infty}\frac{1}{T}(\lambda_1 f_{jk}\mathbb{1}(j<k))_{s\,\in\,Tg_j} = \\ \lambda_1 g_k f_{jk}\int_{(\eta_k-\eta_j)}\Phi(((\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j))+ln(a_k)-ln(a_j))dF(\eta_k-\eta_j) \tag{A.4}$$

Following the same logic, the the expected number of workers per period at employer j receiving and accepting an offer from employer k is

$$\lim_{T\to\infty}\frac{1}{T}(\lambda_1 f_{kj}\mathbb{1}(k>j))_{s\,\in\,Tg_j} = \\ \lambda_1 g_j f_{kj}\int_{(\eta_k-\eta_j)}\Phi(((\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j))+ln(a_k)-ln(a_j))dF(\eta_k-\eta_j) \tag{A.5}$$

while the expected number of workers per period at employer j receiving and rejecting an offer from employer k is

$$\lim_{T\to\infty}\frac{1}{T}(\lambda_1 f_{kj}\mathbb{1}(k<j))_{s\,\in\,Tg_k} = \\ \lambda_1 g_j f_{kj}\int_{(\eta_j-\eta_k)}\Phi(((\tilde{\psi}_j-\tilde{\psi}_k)+(\eta_j-\eta_k))+ln(a_j)-ln(a_k))dF(\eta_j-\eta_k) \tag{A.6}$$

Plugging in all expected offers made in a period by employer k to workers at employer j, which are the offers in equations A.5 and A.6, into the likelihood function of Proposition 1, we obtain the likelihood of all offers received by workers of employer j from employer k as:

$$\mathcal{L} = exp\Big(\int_{(\eta_k-\eta_j)} log(\underbrace{\Phi[(\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j)+ln(a_k)-ln(a_j)]^{g_j f_{kj}\Phi[(\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j)+ln(a_k)-ln(a_j)]*\frac{1}{f_k^{NE}}\frac{1}{g_j}}}_{\text{Accepted offers}} * \\ \underbrace{\Phi[(\tilde{\psi}_j-\tilde{\psi}_k)-(\eta_k-\eta_j)+ln(a_j)-ln(a_k)]^{g_j f_{kj}\Phi[(\tilde{\psi}_j-\tilde{\psi}_k)-(\eta_k-\eta_j)+ln(a_j)-ln(a_k)]*\frac{1}{f_k^{NE}}\frac{1}{g_j}})dF(\eta_k-\eta_j)}_{\text{Rejected offers}}\Big)$$

Where I use that due to the symmetry of η_k and η_j, $dF(\eta_k-\eta_j) = dF(\eta_j-\eta_k)$. We see immediately that g_j cancels out. Furthermore, we can take logs:

$$ln(\mathcal{L}) = \int_{(\eta_k-\eta_j)}\Big(\underbrace{\frac{f_{kj}}{f_k^{NE}}\Phi[(\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j)+ln(a_k)-ln(a_j)]ln(\Phi[(\tilde{\psi}_k-\tilde{\psi}_j)+(\eta_k-\eta_j)+ln(a_k)-ln(a_j)])}_{\text{Accepted offers}}+ \\ \underbrace{\frac{f_{kj}}{f_k^{NE}}\Phi[(\tilde{\psi}_j-\tilde{\psi}_k)-(\eta_k-\eta_j)+ln(a_j)-ln(a_k)]ln(\Phi[(\tilde{\psi}_j-\tilde{\psi}_k)-(\eta_k-\eta_j)+ln(a_j)-ln(a_k)])}_{\text{Rejected offers}}\Big)dF(\eta_k-\eta_j) \tag{A.7}$$

Following the same idea, we can write the log-likelihood of all offers received by workers of employer k from employer j as:

$$ln(\mathcal{L}) = \int_{(\eta_k-\eta_j)} \Big(\underbrace{\frac{f_{jk}}{f_j^{NE}} \Phi[(\tilde{\psi}_j - \tilde{\psi}_k) - (\eta_k - \eta_j) + ln(a_j) - ln(a_k)] ln(\Phi[(\tilde{\psi}_j - \tilde{\psi}_k) - (\eta_k - \eta_j) + ln(a_j) - ln(a_k)])}_{\text{Accepted offers}} +$$
$$\underbrace{\frac{f_{jk}}{f_j^{NE}} \Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + (\eta_k - \eta_j) + ln(a_k) - ln(a_j)] ln(\Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + (\eta_k - \eta_j) + ln(a_k) - ln(a_j)])}_{\text{Rejected offers}} \Big) dF(\eta_k - \eta_j) \tag{A.8}$$

As by Assumption 1 $\frac{f_{kj}}{f_k^{NE}} = \frac{f_{jk}}{f_j^{NE}}$, we have that the likelihood contributions of accepted offers in equation A.7 equals the likelihood contributions of rejected offers in equation A.8. Thus, the total log-likelihood of all binary choices made over offers between employer k and employer j can be written as a function of accepted offers only:

$$ln(\mathcal{L}) = \frac{f_{jk}}{f_j^{NE}} \int_{(\eta_k-\eta_j)} \Big(\underbrace{\Phi[(\tilde{\psi}_j - \tilde{\psi}_k) - (\eta_k - \eta_j) + ln(a_j) - ln(a_k)] ln(\Phi[(\tilde{\psi}_j - \tilde{\psi}_k) - (\eta_k - \eta_j) + ln(a_j) - ln(a_k)])}_{\text{employer-to-employer transitions from employer } k \text{ to } j} +$$
$$\underbrace{\Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + (\eta_k - \eta_j) + ln(a_k) - ln(a_j)] ln(\Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + (\eta_k - \eta_j) + ln(a_k) - ln(a_j)])}_{\text{employer-to-employer transitions from employer } j \text{ to } k} \Big) dF(\eta_k - \eta_j) \tag{A.9}$$

As this holds for any pair of employers $j \in J$ and $k \in K$, it also holds for the joint likelihood of all observed transitions between all employers in J. Consistent estimates of the parameter σ,which is identified, because the coefficient on wage λ is normalized to 1, and the vector of a's are obtained under standard regularity conditions of MLE.[71] QED.

[71] This becomes more clear when canceling out the constant $2\frac{f_{jk}}{f_j^{NE}}$ and ignoring the random part of the wage offer, in which case equation A.9 equals the standard probit likelihood function (with free variance parameter): $ln(\mathcal{L}) = \underbrace{\Phi[(\tilde{\psi}_j - \tilde{\psi}_k) + ln(a_j) - ln(a_k)] ln(\Phi[(\tilde{\psi}_j - \tilde{\psi}_k) + ln(a_j) - ln(a_k)])}_{\text{employer-to-employer transitions from employer } k \text{ to } j} +$ $\underbrace{\Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + ln(a_k) - ln(a_j)] ln(\Phi[(\tilde{\psi}_k - \tilde{\psi}_j) + ln(a_k) - ln(a_j)])}_{\text{employer-to-employer transitions from employer } j \text{ to } k}$. The random part of wage η is required to be non-degenerate for at least one firm in sample to avoid that firms' non-wage value is collinear with firms' wage offer.

F Shrinkage of Non-Wage Values

I rely on the empirical Bayes approach by Morris (1983) for the shrinkage of employers' non-wage values. The following exposition follows Sorkin (2018, Appendix H).

Let j be an employer, and n_J the number of employers. Let $n_{t(j)}$ be the sum of incoming and outgoing transitions of employer j. Let $ln(a_j)$ be employer j's true non-wage value, and $ln(a_j)^{raw}$ be the estimate of employer j's non-wage value. Let Q be the $n_J \times 1$ vector of $ln(a_j)^{raw}$. Let π_j^2 denote the variance of the estimate.[72] Let κ^2 denote the estimate of the true variance of a_j. Let $\boldsymbol{x_j}$ be an $n_x \times 1$ vector of federal state by industry dummies.[73] Let X be the stacked vector of the $\boldsymbol{x_j'}$. Let $\boldsymbol{\lambda_0}$ be a $n_x \times 1$ vector of coefficients. Finally, let w_j the weight of employer j and W be the $n_J \times n_J$ matrix with w_j on the diagonal. These terms relate as follows:

$$w_j = n_{t(j)} \frac{1}{\hat{\pi}_i^2 + \hat{\kappa}^2} \tag{A.10}$$

$$\hat{\kappa}^2 = \max\left\{0, \frac{\sum_j w_j \{\frac{n_J}{n_J - n_x}(ln(a_j)^{raw} - \boldsymbol{x_j'}\hat{\boldsymbol{\lambda}})^2 - \hat{\pi}_j^2\}}{\sum_j w_j}\right\} \tag{A.11}$$

$$\hat{\boldsymbol{\lambda}} = (X^W X)^{-1} X' W Q \tag{A.12}$$

where the two unknowns are $\hat{\kappa}^2$ and $\hat{\boldsymbol{\lambda}}$. These are solved for in the following loop: Initialize $w_j = n_{t(j)}$. Then iterate the following until convergence:

1. Compute $\hat{\boldsymbol{\lambda}}$ using equation A.12
2. Compute $\hat{\kappa}^2$ using equation A.11
3. Check if $\hat{\kappa}^2$ has converged. If not, update the weights, w_j, and return to step 1.

The feasible shrinkage estimator then is:

$$\hat{b}_j = \left(\frac{n_J - n_x - 2}{n_J - n_x}\right)\left(\frac{\hat{\pi}_j^2}{\hat{\pi}_j^2 + \hat{\kappa}^2}\right) \tag{A.13}$$

$$ln(a_j)^{shrinked} = (1 - \hat{b}_j) ln(a_j)^{raw} + \hat{b}_j \boldsymbol{x_j'}\hat{\boldsymbol{\lambda}} \tag{A.14}$$

Where $ln(a_j)^{shrinked}$ is the estimate of employers' non-wage value on which I rely throughout my analyses.

[72] I have a direct estimate of the variance of $ln(a_j)^{raw}$ from my search model. To obtain an estimate of the variance of the AKM each firms' fixed effect, I bootstrap estimate the AKM model 30 times.

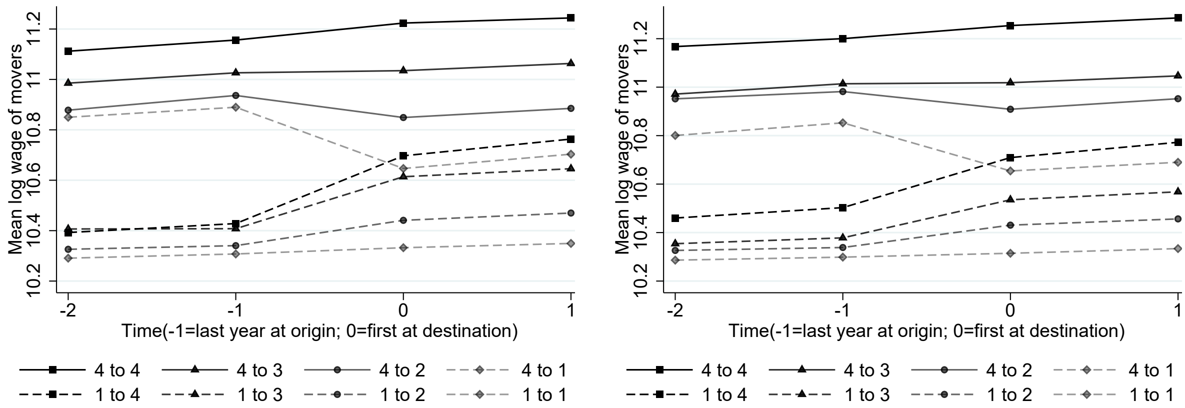
[73] Industry classification: NACE main section (see Table 1). In case there are fewer than 10 employers in a federal state $\times$ industry cell, I merge it with a geographically adjacent federal state. I do so in a loop until there are 10 employers in every cell, or until all federal states of that industry are merged.

G Search Model and AKM

G.1 Specification Check for AKM Wage Model

Figure A.16: EVENT STUDY AROUND JOB MOVES

(a) 1996–2003 Panel (b) 2004–2011 Panel



Notes: The figure shows the evolution of wages of workers who moved from employers in the top and bottom wage quartile groups to destination employers in any of the other quartile groups. The sample is based on workers in column 2 (1996–2003) and column 4 (2004–2011) of Table 1 who were reemployed in the destination employer in the next or the following year following separation from the origin employer, and were employed at the origin and destination employer for 2+ consecutive years. Origin/destination employers are based on the quartile of the average wage of co-workers.

G.2 Estimation of Wage Components

I proceed as follows to decompose the wage and obtain its covariance with job value components. First, I estimate a standard two-way fixed effect model of the following form using reghdfe in Stata (Correia, 2017):

$$ln(w_{it}) = \alpha_i + \boldsymbol{X}'_{it}\beta + \psi_{\boldsymbol{J}(i,t)} + r_{it} \tag{A.15}$$

With the coefficients estimated on age squared, age cubic and the year dummies, I correct the wage for the effects of these variables, that is,

$$\begin{aligned} ln(\tilde{w}_{it}) =& ln(w_{it}) - \beta_{ageSq} * \text{age}^2_{it} - \beta_{ageSq_Female} * \text{age}^2_{it} * \text{female}_i \\ & - \beta_{ageCub} * \text{age}^3_{it} - \beta_{ageCub_Female} * \text{age}^3_{it} * \text{female}_i - \textbf{year}'_{it} * \boldsymbol{\beta_{year}} \end{aligned} \tag{A.16}$$

I then use $ln(\tilde{w}_{it})$ and apply the estimator of Kline et al. (2020) to it, using their MATLAB-package (Kline et al., 2019). This returns unbiased estimates of the following moments:

$Var(\psi_{\boldsymbol{J}(i,t)})$, $Var(\alpha_i)$ and $Cov(\psi_{\boldsymbol{J}(i,t)}, \alpha_i)$. I use these estimates in my decomposition. To calculate the other moments of the variance decomposition including the covariances with employers' non-wage values, I rely on the estimates from reghdfe.[74]

G.3 Nesting AKM Identifying Assumptions in Search Model

As Card et al. (2013, pp. 988–992) show, the critical necessary condition for OLS to identify the parameters of interest in equation 3 is that $\mathbb{E}[f^{j'}r] = 0$, where f^j is a vector of dummies defining the assignment of workers to firms and r is a vector of workers' wage error term. $\mathbb{E}[f^{j'}r] = 0$ holds if the assignment of workers to establishments $\boldsymbol{J}(i,t)$ is strictly exogenous with respect to r:

$$P(\boldsymbol{J}(i,t) = j|r) = P(\boldsymbol{J}(i,t) = j) \;\; \forall i, t \tag{A.17}$$

To see how this condition translates into my search model, consider two firms k and j, and consider workers at k. equation A.17 holds for every worker at k if

$$\begin{aligned}&(\delta_k(1-\rho_k)f_j^{NE} + \delta_k\rho_k f_{jk}) * (\tilde{\psi}_j - \psi_j) - \\ &((1-\delta_k)\lambda_1 f_{jk}) * \left(\int_{\eta_j}\int_{\eta_k}\int_{\epsilon_j}\int_{\epsilon_k} \mathbb{I}((\alpha_{it} + \tilde{\psi}_j + \eta_j) + ln(a_j) + \epsilon_j > \right. \\ &\left. (\alpha_{it} + \tilde{\psi}_k + \eta_k) + ln(a_k) + \epsilon_k) dF(\eta_j)dF(\eta_k)dF(\epsilon_j)dF(\epsilon_k) * (\tilde{\psi}_j - \psi_j + \eta_j) \right) = 0\end{aligned} \tag{A.18}$$

where the terms embraced in the first parenthesis represent the probability that a worker at k makes an exogenous transition to firm j, potentially via non-employment (see workers' value function in Appendix E), and $\tilde{\psi}_j - \psi_j$ describes the wage residual in case of these transitions to employer j (see Section 3.2). The terms embraced in the first paranthesis on the second line of equation A.18 represent the probability that a worker at k does not make an exogenous transition and receives an offer from firm j. The remaining terms represent the wage residual the worker will have if value of the offer from firm j exceeds the value of the offer from firm k, $(\tilde{\psi}_j - \psi_j + \eta_j$.

Intuitively, equation A.18 says that if a worker at k is reassigned to j, the expected wage residual the worker will have at j will be $= 0$. Thus, assuming that A.18 holds for every firm-pair k and j in the sample (including when k=j), the search model indeed nests the condition

[74] The limited mobility bias only affects the three moments which I calculate using the estimator by Kline et al. (2020). For all other variance and covariances of the decomposition calculating them based on the estimates from reghdfe yields consistent estimates.

in equation A.17.[75]

[75]Assuming that the initial state of the search model is that every worker is assigned to a firm and has a wage residual equal to zero.

H Lower Bound for Var(ϵ)

Due to the binary choice made by workers, the distribution of realized ϵ_{it} is truncated below for all workers that have either obtained their job through an employer-to-employer transition or that have rejected at least one job offer from an outside employer since they started working at their current employer. To calculate a lower lower bound on the variance of ϵ_{it}, I assume all workers have received at least one outside offer (or have been hired through an employer-to-employer transition) and estimate the distribution of ϵ_{it} to be truncated from below at -0.421 in the 1996–2003 sample and at -0.410 in the 2004–2011 sample, which equals the average lower bound on ϵ_{it} from all employer-to-employer transitions. I then calculate $Var(\epsilon_{it}|\epsilon_{it} \geq$ lower bound) according to Greene (2000, p. 876). I obtain that $Var(\epsilon_{it}|\epsilon_{it} \geq -0.421) = .032$ for 1996–2003 and $Var(\epsilon_{it}|\epsilon_{it} \geq -0.410) = .034$ for 2004–2011.

I Derviations for Section 4.2

I.1 Rent Dispersion Under Monopsony

In following I show how in a general equilibrium monopsony model rent dispersion can arise due to differences in labor productivity across firms. The following line of reasoning follows the exposition in Manning (2021).

Suppose that, in logs, the revenue of firm j can be written as:

$$y_j = z_j + (1-\eta)ln(g_j) - ln(1-\eta) \tag{A.19}$$

where y_j is log revenue and z_j is a shifter of the revenue function. η captures a parameter that is influenced by returns to scale in the production function and the elasticity of the product demand curve.

Firm j's labor supply in period t is given by:

$$\begin{aligned} g_{j,t} = & \underbrace{(1-\delta_j)g_{j,t-1}}_{\text{no job destruction}} + \underbrace{\bar{f}_j}_{\text{hires from non-employment}} \\ & + \sum_{k=1}^{J} \underbrace{\lambda_1(f_{jk}(1-\delta_k)g_{k,t-1}\Phi((\psi_j + ln(a_j)) - (\psi_k + ln(a_k))}_{\text{hires from employer } k} \\ & - \underbrace{\lambda_1 f_{kj}(1-\delta_j)g_{j,t-1}\Phi((\psi_k + ln(a_k)) - (\psi_j + ln(a_j)))}_{\text{quits to employer } k} \end{aligned} \tag{A.20}$$

that is, the labor supply to firm j in period t equals the share of its labor supply from the previous period that was not exogenously destroyed $(1-\delta_j)g_{j,t-1}$, plus its hires from non-employment $\bar{f}_j$, plus the net hires resulting from workers doing voluntary employer-to-employer transitions. $\Phi()$ denotes the cumulative distribution function of $\mathrm{N}(0, 2\sigma^2)$. We see immediately that g_j is increasing in firm j's value offer $\psi_j + ln(a_j)$. Let's assume that the relationship between $ln(g_j)$ and $\psi_j + ln(a_j)$ is linear and thus write

$$ln(g_j) = \epsilon * (\psi_j + ln(a_j)) \tag{A.21}$$

where ϵ denotes the elasticity of firm j's labor supply with respect to its firm value offer.

The profit-maximizing value offer $\psi_j + ln(a_j)$ will equate marginal cost of one additional unit of labor g_j with the marginal revenue of one additional unit of labor. Thus, taking the derivative with respect to g_j in equation A.19 and combining it with the derivative with respect to $exp(\psi_j)$ in equation A.21, this can be written as:[76]

$$z_j - \eta ln(g_j) = ln(\frac{1+\epsilon}{\epsilon}) - \frac{1}{\epsilon} ln(g_j)$$

and thus, will imply the following level of employment:

$$ln(g_j) = \frac{\eta}{1+\epsilon\eta}(z_j - ln(\frac{1+\epsilon}{\epsilon})) \tag{A.22}$$

where we see immediately that for any η and $\epsilon > 0$, $\frac{\partial ln(g_j)}{\partial z_j} > 0$, and $\frac{\partial(\psi_j + ln(a_j))}{\partial z_j} > 0$ thus more productive firms will have more employees and offer greater value.

I.2 Effect of a Decrease in Labor Supply Elasticity on Rent Dispersion

Consider firms' labor supply given by equation A.21. More productive firms offer greater value, that is, $\frac{\partial(\psi_j + ln(a_j))}{\partial z_j} > 0$. Thus, a sufficient condition for an decrease in labor supply elasticity to increase rent dispersion across firms is that $\frac{\partial^2(\psi_j + ln(a_j))}{\partial\epsilon\partial z_j} < 0$. Note that:

$$\frac{\partial^2(\psi_j + ln(a_j))}{\partial\epsilon\partial a_j} = -\frac{\eta(1+2\epsilon\eta)}{(\epsilon(1+\epsilon\eta))^2} \tag{A.23}$$

which is strictly negative for any η and $\epsilon > 0$.

I.3 Effect of Increase in Search Frictions on Labor Supply Elasticity

Consider firms' labor supply given by equation A.20, and suppose in $t-1$ all firms are equally of size and make each other equally many offers ($g_{j,t-1} = 1$ and $f_{jk} = 1$ for all j and k), and that there is no job destruction and no hires from non-employment.

Then equation A.20 simplifies to

$$g = J\lambda_1 f(2\Phi((\psi_j + ln(a_j)) - (\psi_k + ln(a_k))) - 1)$$

Where J denotes the number of firms in the economy. I will omit the constants J and f in what follows. The labor supply elasticity then is

[76] Here, I assume that $exp(\psi_j)$ captures the full wage of a worker at firm j. Then, by the envelope theorem, the marginal cost of increasing ψ_j will equal the marginal cost of increasing total firm value $\psi_j + ln(a_j)$.

$$\frac{\partial ln(g)}{\partial g}\frac{\partial g}{\partial(\psi_j + ln(a_j))} = \frac{2}{g}\lambda_1\phi((\psi_j + ln(a_j)) - (\psi_k + ln(a_k))) \tag{A.24}$$

where $\phi()$ denotes the probability density function of $\mathrm{N}(0, 2\sigma^2)$.

An increase in search frictions is reflected by a decrease in the frequency with which workers are receiving offers λ_1. The impact of λ_1 on the labor supply elasticity is:

$$\frac{\partial \frac{\partial ln(g)}{\partial g}\frac{\partial g}{\partial(\psi_j+ln(a_j))}}{\partial \lambda_1} = \frac{2}{g}\phi((\psi_j + ln(a_j)) - (\psi_k + ln(a_k))) \tag{A.25}$$

Indeed, equation A.25 is strictly positive. Thus, if λ_1 decrease (more search frictions), the elasticity of labor supply decreases.

I.4 Effect of Decrease in Segregation on Labor Supply Elasticity

Consider firms' labor supply elasticity given by equation A.24. A decrease in segregation implies that workers receive offers from firms that are more different than their current one in terms of the value they offer, which means that $|(\psi_j + ln(a_j)) - (\psi_k + ln(a_k))|$ in equation A.24 increases. Substituting $(\psi_j + ln(a_j)) - (\psi_k + ln(a_k))$ with ΔV, we thus have:

$$\frac{\partial \frac{\partial ln(g)}{\partial g}\frac{\partial g}{\partial(\psi_j+ln(a_j))}}{\partial |\Delta V|}\Bigg|\Delta V \geq 0 = -\frac{2}{g}\lambda_1\phi(\Delta V)\frac{\Delta V}{\sqrt{(}2)\sigma} \tag{A.26}$$

and

$$\frac{\partial \frac{\partial ln(g)}{\partial g}\frac{\partial g}{\partial(\psi_j+ln(a_j))}}{\partial |\Delta V|}\Bigg|\Delta V < 0 = \frac{2}{g}\lambda_1\phi(\Delta V)\frac{\Delta V}{\sqrt{(}2)\sigma} \tag{A.27}$$

Where equation A.26 and A.27 are strictly negative. Thus, a decrease in segregation leads to a decrease in labor supply elasticity.

I.5 Effect of Increase in Idiosyncrasy of Preferences on Labor Supply Elasticity

Consider firms' labor supply elasticity given by equation A.24. An increase in the idiosyncrasy of workers' preferences es reflected in my model by an increase in σ. Thus, we are interested in:

$$\frac{\partial \frac{\partial ln(g)}{\partial g} \frac{\partial g}{\partial(\psi_j + ln(a_j))}}{\partial \sigma} = \frac{\sqrt(2)}{g} \lambda_1 \phi(\psi_j + ln(a_j)) - (\psi_k + ln(a_k)) \frac{(\psi_j + ln(a_j)) - (\psi_k + ln(a_k))^2 - 2\sigma^2}{2\sigma^3} \tag{A.28}$$

which is negative if

$$2\sigma^2 > (\psi_j + ln(a_j)) - (\psi_k + ln(a_k))^2 \tag{A.29}$$

I use the offer distribution for the 1996–2003 panel I estimate in Appendix J to evaluate whether it is plausible to expect that inequality A.29 holds, and a increase in the idiosyncrasy of preferences will decrease labor supply elasticity. While I find that inequality A.29 holds only for close to half of all offers, I still find that the derivative in equation A.28 is negative when summing over all offers, because $\phi(\psi_j + ln(a_j)) - (\psi_k + ln(a_k))$ is much greater for offers with low $|(\psi_j + ln(a_j)) - (\psi_k + ln(a_k)|$. I thus conclude that the increase in idiosyncrasy in preferences likely lead to a reduction of labor supply elasticity.[77]

I.6 Firms' Cost Minimization in Value Provision

Employers solve:

$$\min_{\psi_j, a_j} c_j(a_j) + exp(\bar{\alpha}_j + \psi_j) \qquad s.t.\ \ \psi_j + ln(a_j) = V_j^E$$

where $\bar{\alpha}_j$ denotes the average wage component net of the firm-specific component of every worker at firm j. The cost-minizing quantities of $ln(a_j)$ and ψ_j thus solve:

$$ln(a_j^*) = \frac{V_j^E - ln(c'(a_j^*)) + \bar{\alpha}_j}{2} \qquad \psi_j^* = \frac{V_j^E + ln(c'(a_j^*)) - \bar{\alpha}_j}{2}$$

meaning I can estimate the log of employers' marginal cost of non-wage value provision using

$$ln(c'(a_j^*)) = \psi_j - ln(a_j) + \bar{\alpha}_j$$

and replacing the right-hand-side terms with the estimates from my search model and the AKM regression. Figure A.4 summarizes the marginal cost of non-wage value provision on the industry-level.

[77] An additional argument in favor of a decrease of labor supply elasticity is that measurement error in my empirical estimates inflates $(\psi_j + ln(a_j)) - (\psi_k + ln(a_k))^2$.

J Estimating the Distribution of Offers

In my search model I assume that (see Assumption 1)

$$\sum_{k \in J} f_{jk} g_k = f_j^{NE} \quad \forall j \in J \tag{A.30}$$

that is, that I can estimate the total number of offers firm j makes equals the number of workers firm j hires from non-employment f_j^{NE}.[78] Moreover, I assume that

$$\frac{f_{jk}}{f_j^{NE}} = \frac{f_{kj}}{f_k^{NE}} \;\; \forall j, k \in J \tag{A.31}$$

that is, the ratio of intensities with which firm j and k make offers to each others' workers must be equal to the ratio of the intensities with which they hire from non-employment.

There does not necessarily exist unique solution (unique vector $f_{(j*k \times 1)}$) to the system of equations implied by equations A.30 and A.31.

A feasible way of estimating f is

$$\min_{f_{(j*k\times 1)}} \sum_{j \in J} \Big(\sum_{k \in J} f_{jk} g_k - f_j^{NE} \Big)^2 \;\text{ s.t. }\; \frac{f_{jk}}{f_j^{NE}} = \frac{f_{kj}}{f_k^{NE}} \;\; \forall j, k \in J \tag{A.32}$$

that is, to minimize the quadratic difference of the total number of offers made by firm j to employees of any other firm k, minus the total number of offers firm j has made, as estimated from the hires from non-employment, subject to equation A.31.

I solve the minimization problem equation A.32 separately for the 1996–2003 and the 2004–2011 sample.[79]. The resulting solution for the total number of offers implied by $\sum_{k \in J} f_{jk} g_k$ is remarkably close to f_j^{NE} (correlation of 1.00 in both sample periods).

[78] More precisely, I assume that $\sum_{k \in J} f_{jk} g_k = a * f_j^{NE} \quad \forall j \in J$, where I set, w.l.o.g., $a = 1$ in equation A.30 to ease exposition.

[79] I use the quadprog command in MATLAB. I only estimate f_{jk} if firm j and k are connected to each other by at least one employer-to-employer transition. Otherwise, I assume firm j and k are unconnected and thus set $f_{jk} = 0$