Firms, Productivity, and Returns to Tenure*

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I study how the returns to tenure vary across firms with different levels of productivity and how this affects wage dispersion and the cost of job loss. Using an extension of Abowd et al. (1999) and Danish administrative data, I find that workers at more productive firms tend to see larger increases in wages over time. In contrast, starting wages are only weakly related to firm productivity. I show that these differences across firms are not due to composition effects or "quick learner" workers sorting into productive firms, but are a causal effect of being employed at a productive firm. A third of these gains from tenure are portable when switching employers even when separating involuntarily, indicating that these differences in returns partly reflect heterogeneity across firms in the rate at which employees acquire general human capital. Worker mobility patterns suggest that non-portable gains are primarily driven by differences in the rate of learning about worker-firm match quality. Finally, I show that firm-specific returns significantly influence the cost of job loss, with a real earnings loss nearly twice as large for workers displaced from firms in the top quartile of the returns distribution compared to those from the bottom quartile.

JEL Classification: J24; J31

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1. Introduction

In this paper, I revisit two well-established empirical facts: (i) in the cross-section, workers with longer tenure receive higher wages;[1] and (ii) in the cross-section, workers at more productive firms earn higher wages.[2] I show that these empirical facts are connected and that examining firms is key to understanding returns to tenure. I also show that the firm heterogeneity in returns to tenure are an an important driver of the cost of job loss.

The primary contribution of the paper is documenting that the cross-sectional relationship between wages and productivity is about half as strong for starting wages as it is for wages of workers with above-median tenure, based on Danish administrative data. This relationship implies that in the cross-section, returns to tenure are higher at more productive firms. However, this finding could be entirely due to sorting and composition effects (e.g. productive firms hire "quick learners"). To address this, I estimate firm-specific returns to tenure and show that the differences in returns are not driven by sorting or compositional effects, but are truly firm-specific. These firm-specific returns to tenure, in turn, play a significant role in explaining the loss of earnings when workers are displaced in mass-layoff events, with a real earnings loss nearly twice as large for workers displaced from firms in the top quartile of the returns distribution compared to those from the bottom quartile.

In addition, I make two secondary contributions. First, I show that approximately one-third of the returns to tenure are portable across firms, meaning that workers retain part of the wage growth associated with tenure even after changing employers. The portability share remains remarkably constant across low- and high-productivity firms. The other secondary contribution is to examine the underlying mechanisms driving the differences in returns to tenure and the relationship with productivity. I find that differences in general human capital accumulation and the process of learning about job match quality are the most important drivers of the differences in returns to tenure.

To estimate the firm-specific returns to tenure, I extend the two-way fixed effects approach developed by Abowd et al. (1999). While their approach decomposes individual wages into worker and firm effects, I additionally allow the firm effect to vary across tenure groups. The inclusion of the worker effect ensures that all identifying variation

[1] Mincer and Jovanovic (1981); Brown (1989); Topel (1991); Bagger et al. (2014).

[2] Nickell and Wadhwani (1990); Abowd and Lemieux (1993); Card et al. (2016); Di Addario et al. (2023).

for the firm-tenure effects comes from workers either moving up the tenure ladder within a firm or starting anew at a different firm, rather than, for example, high-wage workers simply staying longer at the same firm. The result is a coarse non-parametric firm-specific curve for returns to tenure.

I find that firms play a significant role in the overall dispersion of returns to tenure, with the standard deviation of the estimated returns being close to half that of individual returns, after accounting for pure age effects. The estimates also imply that workers with above-median tenure have an hourly wage close to 15 log points higher than their zero-tenure coworkers at firms in the top 10% most productive firms, compared to less than 5 log points more at the bottom 10% least productive firms. Overall, the well-established positive relationship between wages and firm productivity (Nickell and Wadhwani 1990; Card et al. 2016) is primarily driven by the wages of high-tenure workers. Additionally, I find that the same is true for the relationship between wages and firm size (Brown and Medoff 1989).

In my extended AKM model, the simplest composition effects are captured by the worker fixed effect. However, it is still possible that "quick learners", who tend to experience high returns to tenure at any firm, sort into more productive firms. To address this, I estimate a variation of the firm-tenure effects using only workers who achieve the same level of tenure at two different firms throughout their careers. This is equivalent to allowing for both worker-specific and firm-specific returns to tenure. The results are nearly identical, indicating that the differences in the returns to tenure are not due to sorting on worker-specific returns to tenure. Alternatively, firms and workers could also be sorting based on match-specific returns. If workers tend to choose firms where the match-specific returns to tenure are high, we would expect that a worker moving from a generally high-returns firm to a low-returns firm would experience a smaller change in returns compared to a worker moving in the opposite direction. I find no sign of this type of asymmetry.[3] I conclude that the estimates of the firm-specific returns to tenure are not driven by sorting in hiring but are truly firm-specific.

Next, I examine the long-term effects of differences in returns by estimating the portability of returns to tenure across firms. To do so, I add "origin" firm-tenure effects to the model, similar to the "origin" firm effects used by Di Addario et al. (2023). The origin firm-tenure effects capture the impact on wages at a worker's current firm of having previously achieved a specific tenure level at another specific firm. Using this

[3] This is the equivalent tenure-version of the symmetry test from Card et al. (2016) for the AKM model.

approach I find that a third of the returns to tenure are portable. Portability is not affected by switching industries or occupations, and the share of portable returns is stable across productivity levels.

I then examine the drivers of heterogeneity in returns to tenure and their relationship with productivity. The fact that part of the returns is portable indicates that differences in general human capital accumulation could be important (Becker 1962; Arellano-Bover and Saltiel 2024). However, if firms compete for workers through offers and counteroffers, other factors could appear portable (Lazear 2009; Postel–Vinay and Robin 2002). I show that 90% of the portable part of returns remains even if the employee left the original job involuntarily. This rules out portability being driven by workers having a better bargaining position. Additionally, I show that sequential auction models such as Postel–Vinay and Robin (2002) predict that the expected returns to tenure for a poached worker will depend negatively on the productivity of the firm the worker was poached from. I find no empirical evidence to support this prediction in the data.

I also examine the mechanisms behind the non-portable part of the returns. Possible explanations include firm-specific capital accumulation, wage-tenure contracts (Burdett and Coles 2003), and learning about match quality (Jovanovic 1979). I follow Nagypál (2007) and study how the gap in separation rates between tenure groups reacts to negative firm-level shocks. Based on the predictions of these theories, I find suggestive evidence that the primary source of heterogeneity in non-portable returns is how workers and firms learn about the quality of their match.

Finally, it is well-documented that tenure and the cost of job loss are connected (Topel 1991; Jacobson et al. 1993). Having established heterogeneity in firm-specific returns to tenure, it follows directly that these differences might also drive variations in the cost of job loss. Following the mass-layoff event-study literature (Davis and Von Wachter 2011; Lachowska et al. 2020; Bertheau et al. 2023), I examine how earnings losses for highly tenured workers after displacement are influenced by their employer's firm-specific returns. I find that workers displaced from firms in the top quartile of returns face an earnings loss 80% greater in the first year than those from firms in the lowest quartile. After three years, earnings losses for workers from low-return firms drop to 0.03 log points, while losses for those from high-return firms only fall to 0.1 log points. These results highlight the significant role of firm-specific returns to tenure in driving heterogeneity in the cost of job loss, suggesting that policymakers should consider this factor when designing polices to mitigate the losses.

Related literature and contribution: This paper contributes to the extensive literature on wage dispersion driven by firm and industry heterogeneity, dating back to Slichter (1950) and expanded by many others, including Krueger and Summers (1988); Abowd et al. (1999); Nickell and Wadhwani (1990); Abowd et al. (2006); Card et al. (2013, 2016); Bonhomme et al. (2019).[4] These studies have documented wage-dispersion across firms or industries and how it relates to firm and industry characteristics, including productivity. I contribute to this literature by documenting that the majority of the correlation between these firm-specific wage premia and productivity and other key firm characteristics is actually driven by firm-specific returns to tenure and that these returns are not the product of sorting or composition effects, but are innate characteristics of the firm.

This paper also contributes to the literature on estimating the returns to tenure (Mincer and Jovanovic 1981; Altonji and Shakotko 1987; Topel 1991; Dustmann and Meghir 2005; Buhai et al. 2014), as well as understanding the mechanisms driving the returns to tenure, such as accumulation of human capital (Becker 1962; Arellano-Bover and Saltiel 2024), learning about match quality (Jovanovic 1979; Moscarini 2005; Nagypál 2007), frictions and bargaining (Postel–Vinay and Robin 2002; Cahuc et al. 2006; Bagger et al. 2014) and efficient wage-contracts (Lazear 1979; Burdett and Coles 2003; Stevens 2004). In this paper, I document the existence of firm-specific returns to tenure, and find that they are primarily driven by general human capital accumulation and workers and firms learning about the quality of their match.

Finally, this paper also contributes to the literature on the cost of job loss. This includes the strand of research that documents the connection between tenure and earnings losses (Topel 1990; Jacobson et al. 1993), as well as the strand that considers the impact of firm-specific wage components on earnings losses (Lachowska et al. 2020; Bertheau et al. 2023).

The rest of the paper is structured as follows: Section 2 describes the institutional setting and the administrative data. In Section 3, I describe the estimation of the firm-specific returns to tenure and present resulting estimates. In Section 4, I estimate the portability of the returns. In Section 5 and 6 I examine the mechanisms driving the differences in the portable and non-portable parts of the returns to tenure. In Section 7

[4] (Abowd et al. 2006) also estimate heterogeneity in returns to tenure, but within a more strictly parameterized framework than the one used in this paper.

show how the cost of job loss is affected by firm-specific returns to tenure. Section 8 concludes.

2. Data

In this section, I describe the data sources used in the analysis and the sample restrictions. Appendix A provides a detailed overview of the data sources.

Institutional Setting: The Danish labor market is characterized by a high degree of flexibility, both in terms of employment flows and wage setting. Employment, long-term unemployment, and labor market turnover are comparable to the U.S. (Kreiner and Svarer 2022). Most private-sector workers (87%) are covered by collective agreements, but 80% of those covered only face a bargained wage floor, which is non-binding for most workers, or no bargained wage at all. In practice, wages for these workers are negotiated locally at the firm level (DA 2018), allowing firms to engage in the type of wage-setting behavior analyzed in this paper.

Data Sources: The analysis is based on Danish administrative data registries maintained by Statistics Denmark (DST). The primary registry used is the BFL registry, a monthly matched employer-employee dataset containing information on earnings, wages, and hours. Additionally, I draw on the BEF, IDAP, and UDDA registries for demographic information, worker characteristics, and educational background. Firm-level accounting data on revenue, profits, and value-added is sourced from the FIRM registry.

I also incorporate data on the centrality of wage bargaining provided by the Danish Employers Association (DA). Collective agreements typically fall into three categories: a set wage (Normalløn), a wage floor (Minimalløn), or no wage requirements. The DA data specifies the prevailing wage-bargaining scheme at the industry-occupation level.

Sample Restrictions: The sample from BFL includes employment data from 2010 to 2019 at the monthly level, which I aggregate to yearly data. I exclude all person-year observations for which I do not have valid age and education information. I restrict the analysis to individuals in the age range from 20 to 60. Furthermore, I drop observations with less than 3 months of employment, or an hourly wage of less than 60 DKK (8.04 EUR) corresponding to roughly 50% of the bargained minimum wage for unskilled workers. Observations with extreme hourly wages are also excluded (Above 1000 EUR). Additionally, only jobs at firms with at least 10 worker moves in or out of the firm in the sample period.[5] In cases where individuals hold multiple jobs in the same year, only the job with the highest earnings is retained. Finally, I remove workers who leave a firm and return at a later point, since this makes the interpretation of tenure ambiguous.

All wages and accounting statistics are deflated to 2010 prices using the Danish CPI, provided by DST, and converted to euros (1 DKK = 0.134 EUR).[6] Table 1 contains descriptive statistics by tenure. For all results reported using accounting data I also restrict the sample to firms with at least a mean value-added per worker of 200k DKK (26.8k EUR) over the sample period. Note that this restriction is imposed after the estimation of the firm-tenure effects to maintain a large connected set of firms.

Measuring Tenure: BFL does not directly provide information on tenure, so I infer it from the data. Initially, I calculate the cumulative number of years a worker has been employed at a firm, based on the period I observe them in the data. This calculation is performed before applying sample restrictions, except for the age limitation. This approach works well for job matches that begin during the sample period. However, for ongoing matches at the start of the sample, this method tends to underestimate tenure.

To address this, I supplement the BFL data with additional information from IDAN, another employer-employee dataset maintained by DST, which includes employment records from 2000 onward. For workers already employed at a firm in 2010 (the first year of the BFL data used), I add any additional years of tenure observed in IDAN. Since all workers with recalls are excluded, firm tenure and current match tenure are identical in this analysis.

[5] This restriction is imposed to reduce limited mobility bias when estimating firm-specific returns to tenure (Andrews et al. 2008). Additionally, all estimated variance components will be bias-corrected as in Kline et al. (2020)

[6] The Danish Krone is pegged to the Euro and the conversion rate has been stable for the entire sample period.

TABLE 1. Summary Statistics by Sample Restrictions

	Pooled Sample	No Tenure	1-2 years	3 years or more
Panel (a): Base Restrictions				
Number of observations	19,978,546	2,445,481	5,440,104	12,092,961
Number of individuals	2,811,223	1,556,828	2,059,118	2,120,129
Number of person-firm matches	5,302,875	2,445,481	3,445,479	2,620,536
Number of firms	95,033	91,369	93,799	87,111
Number of firm-tenure fixed effects	272,279	91,369	93,799	87,111
Mean log hourly wage	3.254	3.106	3.186	3.314
Std. Dev. of log hourly wage	0.354	0.365	0.367	0.331
Mean tenure (Years)	6.098	0.0	1.426	9.432
Median tenure (Years)	4.0	0.0	1.0	7.0
Panel (b): Base Restrictions, Private Sector, Accounting Data and all Tenure Groups				
Number of observations	9,479,861	1,342,157	2,858,163	5,279,541
Number of individuals	1,628,423	926,482	1,195,402	1,058,990
Number of person-firm matches	2,770,519	1,342,157	1,819,651	1,280,023
Number of firms	57,937	57,937	57,937	57,937
Number of firm-tenure fixed effects	173,811	57,937	57,937	57,937
Mean log hourly wage	3.268	3.129	3.201	3.339
Std. Dev. of log hourly wage	0.374	0.36	0.378	0.358
Mean tenure (Years)	5.409	0.0	1.421	8.943
Median tenure (Years)	3.0	0.0	1.0	7.0
Mean log value added per worker	4.145	4.09	4.113	4.176
Std. Dev. of log value added per worker	0.379	0.383	0.388	0.371

Note: Sample 1a consists of all person-year observations remaining after applying the basic sample restrictions described in Section 2. Sample 1b consists of observations in Sample 1a belonging to private sector firms, for which value-added data is available and exceeds 26.8k EUR per worker, and for which observations in all tenure groups exist.

3. Measuring Heterogeneity in Returns to Tenure

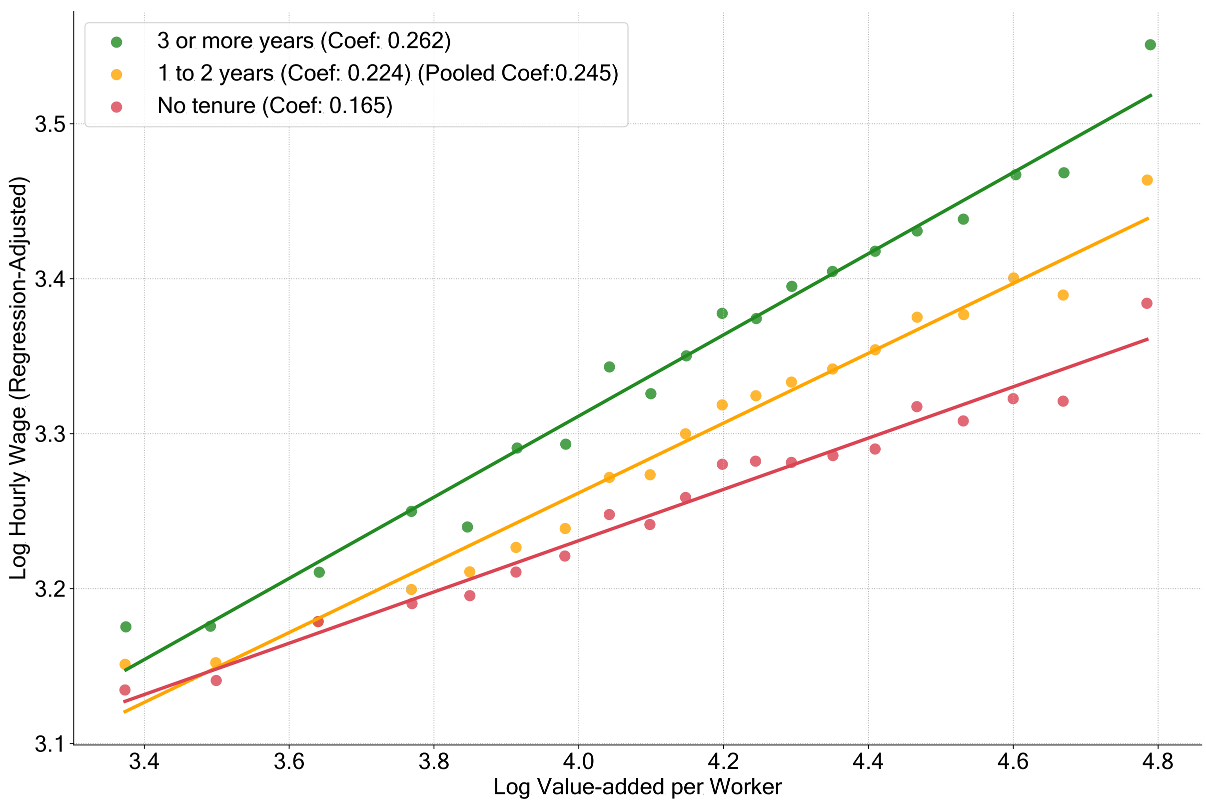
Returns to Tenure and Productivity - Descriptives: The fact that firm productivity and wages are positively correlated has been documented in many different settings including the U.S, Portugal and Italy and using different measures of productivity such as profits or value-added per worker (Nickell and Wadhwani 1990; Abowd and Lemieux 1993; Card et al. 2016; Di Addario et al. 2023). Similarly, it is well-documented that in the cross-section, workers with more tenure tend to get higher wages (Mincer and Jovanovic 1981; Brown 1989; Topel 1991; Bagger et al. 2014). The two empirical facts also hold for the Danish labor market as seen in Figure B.1.

In this paper, I argue that these correlations are connected. To motivate why this is a sensible hypothesis, Figure 1 plots the relationship between regression-adjusted wages and value-added per worker for three tenure groups, *No tenure, 1-2 years of tenure* or *3+ years of tenure*.[7] The main takeaway is the large difference in slopes between groups. While wages tend to be higher at more productive firms at all tenure levels, the relationship is 60% steeper for the wages of workers with 3+ years of tenure and 50% steeper when all tenure groups are pooled compared to that of starting wages. This implies that the cross-sectional returns to tenure are higher at more productive firms. The difference in wages between the high- and low-tenure groups is around 0.15 log points at firms in the top decile of the value-added per worker distribution and less than 0.05 log points in the bottom decile.

Estimating Firm-Specific Returns to Tenure: While Figure 1 shows that the difference in wages between high and low tenure workers is larger at more productive firms in the cross-section, the relationship does not need to reflect the causal effect on returns of being at a more productive firm. It might even not reflect the actual changes in wages over time for the individual workers but could simply be due to composition effects. If more productive workers are more likely to work at productive firms and tend to switch jobs less often, the same pattern would likely emerge, even if firms did not affect the returns to tenure directly. To get a simple measure of firm-level returns to tenure

[7] The choice of these 3 groups is based on two considerations. First, many of the methods used in the following sections will use workers who achieve a certain tenure level at two different firms, and having too many groups would lead to too few observed moves. Second, as seen in Figure B.1 the returns to tenure appear to taper off around 3-5 years. For methods where the few movers are not an issue, I also perform robustness checks using more groups.

FIGURE 1. Log Hourly Wages vs. Log value added per worker



Note: This figure reports mean regression-adjusted log hourly wage by vingtiles of mean log value added per worker. Log hourly wages are residualized via an OLS regression including education-specific year dummies and education-specific cubic polynomials in age. The sample is described in Table 1b. Projection slopes are obtained from regressing regression-adjusted log hourly wages on log value added per worker in the microdata. Pooled coefficient is obtained from a sample pooling all observations regardless of tenure group. All statistics are weighted by firm-size.

that relies on the wage changes of individual workers and allows for this simple type of composition effect, I extend the two-way fixed effects framework from Abowd et al. (1999) (AKM). Instead of decomposing wages into worker and firm effects, I estimate worker and firm-tenure effects, using the same groupings as above. The observed wage for worker i at time t is then decomposed as

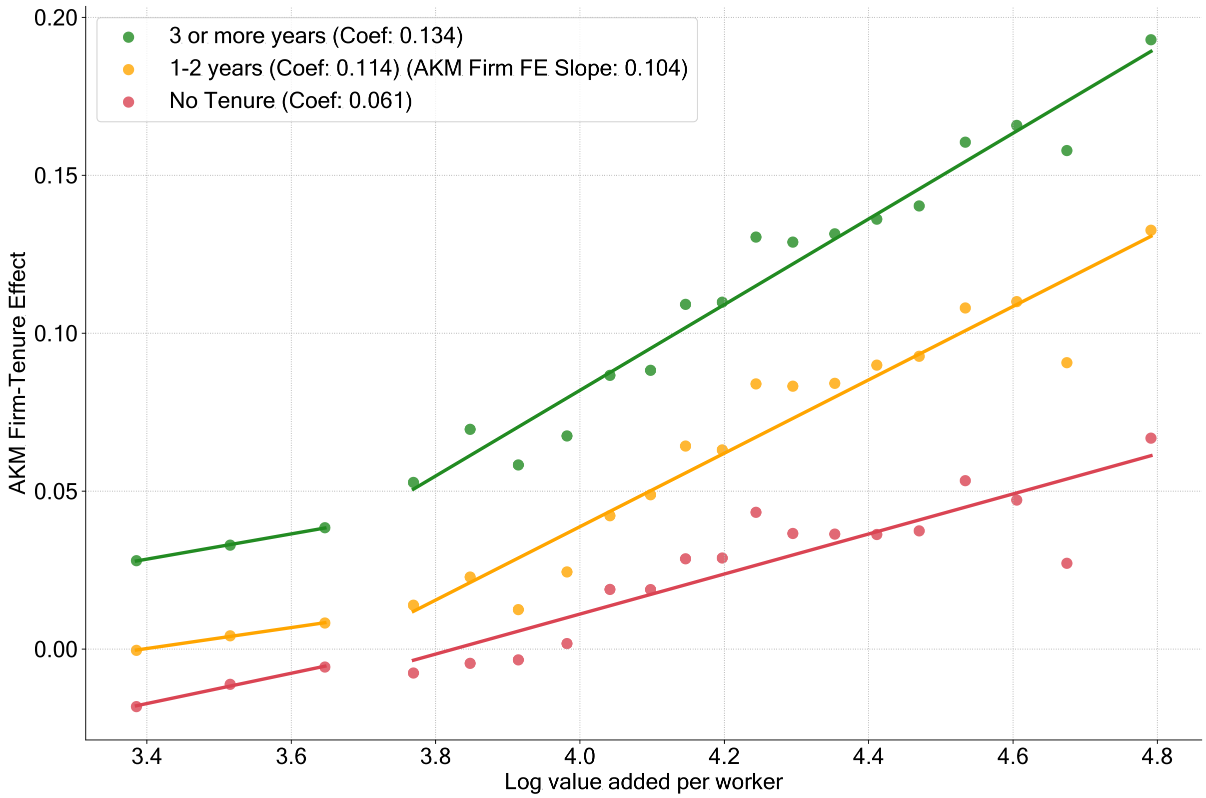
(1) $$y_{it} = \alpha_i + \psi_{\mathbf{j}(i,t)\mathbf{k}(i,t)} + x'_{it}\beta + \varepsilon_{it}$$

where $\mathbf{j}(i,t) \in \{1, \ldots, J\}$ is a function returning the identity of of the firm employing the worker i in year t and $\mathbf{k}(i,t) \in \{L, M, H\}$ is a function returning the tenure group of the worker i in year t, with the possible groups being "No Tenure", "1-2 Years" and "3+ Years". y denotes log hourly wage, α_i is the worker effect of worker i and ψ_{jk} denotes the firm-tenure effect at firm, j, for tenure-group, k, and x'_{it} is a set of observable characteristics, which includes education-year dummies and education-specific cubic polynomials in age, similarly to Card et al. (2016). The inclusion of the worker effect implies that all identifying variation for these firm-tenure effects comes from workers moving up the tenure ladder within a firm, or moving to the start of it at a new firm. The estimated firm-tenure effects will therefore not be biased by sorting on fixed characteristics, such as fixed higher worker productivity. The inclusion of the worker effect also means that it is only possible to identify the relative firm-tenure effects within a connected set of firm-tenure cells (Abowd et al. 1999). I restrict the analysis to the largest leave-one-out connected set of firm-tenure cells in order to estimate bias-corrected variance components and standard errors as described in Kline et al. (2020). Descriptive statistics for the resulting sample is provided in Table D.1.

Figure 2 shows the estimated firm-tenure effects plotted against the log mean value added per worker at the firm. There are two main takeaways from the figure: First, the estimated fixed effects exhibit the same kinked "hockey stick" relationship with value-added as found in Card et al. (2016), with a flatter relationship between wages and value-added on the "zero-surplus frontier" and a steeper positive relationship after some threshold is crossed. The second takeaway, which is the focus of this paper, is the diverging slopes after the kink for the high- and low-tenure effects. The difference in wages between high and low-tenure workers, net of time-invariant worker characteristics, tends to be higher for more productive firms, with the slope being more than 2 times steeper for high-tenure workers. The difference in wages between the high- and low-tenure groups is close to 0.15 log points at firms in the top decile of the value-added per worker distribution and less than 0.05 log points in the bottom decile, basically the same difference as in Figure 1.

Table C.1 reports the same slope as Figure 2 with standard errors, and confirms that the differences in slopes are statistically significant. This is also the case when including tenure-group-by-industry fixed effects in the regression model. Additionally, Table C.2 also includes the coefficients obtained when projecting the estimated firm-tenure effects on log mean firm size. Previous work has found a correlation between size and firm-wage premia (Brown and Medoff 1989; Bloom et al. 2018). The estimates show that the relationship between firm effects and firm size is primarily driven by the wages of high-tenure workers, as the slope for "3+ Years" firm-tenure effects is twice as steep as

FIGURE 2. AKM Firm-Tenure FEs vs. Log value added per worker



Note: This figure reports means of the estimated firm-tenure effects (ψ_{jk} in Eq. 1) by vingtiles of mean log value added per worker. Firm-tenure effects are estimated jointly in a pooled sample. The sample is described in Table D.1b. Projection slopes are obtained from regressing firm-tenure effects on log value added per worker in the microdata for firms with mean log value-added per worker above the kink (3.75). All statistics are weighted by average firm-size over sample period.

that for "No Tenure" firm-tenure effects.

Table 2a reports the AKM variance decomposition of log hourly wages based on Eq. 1 using either firm effects or firm-tenure effects. The explained variance of the AKM effects increases by 20% when when using firm-tenure effects compared to just firm effects. This is not a huge increase, but it is important to note that tenure groups are not of equal size: Only around 10% are in the "No Tenure" group. The standard AKM firm effect is, therefore, already capturing a large part of the differences in wages for workers with tenure. This does not mean that differences in returns to tenure are unimportant, just that most workers have some tenure.

To show this, Table 2b reports means and variance components for individual starting wages and returns to tenure, along with their firm-size weighted counterparts based on the estimated firm-tenure effects.[8] The variance components derived from the estimated effects are bias-corrected as described in Kline et al. (2020). The estimates indicate that firm-specific returns account for a significant portion of the overall dispersion in returns, with the standard deviation of firm-specific returns being about half that of individual returns to tenure. Furthermore, the standard deviation of firm-specific returns is 85% of the standard deviation of firm-specific starting wage premia. This highlights the importance of considering firm-specific returns when examining overall returns and firm-level wage setting.

[8] Individual log hourly wages are residualized via an OLS regression including education-specific year dummies and education-specific cubic polynomials in age.

TABLE 2. Dispersion in Wages and Firm Tenure Effects

Panel (a): AKM variance decomposition of wages

	Firm Effects	Firm-Tenure Effects
Std. Dev. of Log Hourly Wages	0.373	0.373
Std. Dev. of Log Hourly Wages (Residualized)	0.312	0.312
Number of estimated effects	51,028	153,084
Std. Dev. Fixed Effects	0.099	0.111
Std. Dev. Fixed Effects (Bias-Corrected)	0.097	0.107
Fixed Effects Variance Relative to Firm Effects	1.0	1.205

Panel (b): Dispersion in Individual and AKM Returns to Tenure

	Starting Wage	Returns to Tenure
Individual Log Hourly Wages		
Mean	-	0.077
Std. Dev.	0.301	0.217
Estimated Firm-Tenure Effects		
Mean	-	0.076
Std. Dev.	0.112	0.100
Std. Dev. (Bias-Corrected)	0.106	0.089

Note: Panel (a) reports the variance decomposition after fitting an AKM model as in Eq. 1 with either firm effects or firm-tenure effects to log hourly wages only using the estimation sample defined in Table D.1b. Bias-corrected variance components are estimated using the leave-out bias correction of Kline et al. (2020) via leaving a worker–firm via leaving a worker–firm-tenure match out. match out. Panel (b) reports means and variance components for individual starting wages and returns to tenure and employment weighted means and bias-corrected variance components for the estimated firm-tenure effects. The sample is described in Table D.1b. Individual returns are calculated as the difference in mean log hourly wage at "3+ Years of Tenure" and "No Tenure" for each worker-firm match where both means are observed. Log hourly wages are residualized via an OLS regression including education-specific year dummies and education-specific cubic polynomials in age. The returns to to tenure implied by the estimated effects are given by $\psi_{jH} - \psi_{jL}$ from Eq. 1 where H and L indicates "3+ Years of Tenure" and "No Tenure". Note that the means for starting wages are not identified due to the residualization. The bias-corrected FE variance components are estimated using the bias correction of Kline et al. (2020) via leaving a worker–firm-tenure match out.

Additional Specifications: The choice of 3 tenure groups is made to ensure methods that require a sufficient number of workers who achieve a certain tenure level at two different firms are observed. Figure B.2 replicates Figure 2 where the "3+ Years" group has been split into three distinct groups, for a total of five groups. From the figure, it is clear that the majority of returns to tenure already materialize at 3-4 years of tenure, and the baseline specification with three tenure groups is used for the remainder of the paper. Table C.3 reports the changes in log hourly wages across the different tenure groups in response to changes in log value added per worker. Consistent with the findings from Figure 2, the results show that workers with 3+ years of tenure experience a larger wage increase compared to starting wages when firm productivity rises.

Does Sorting Drive Firm-Tenure Fixed Effects?: Even though the approach used for Figure 2 controls for time-invariant worker characteristics, these patterns could still be caused by factors that are not innate to the firm. If "quick learners", who tend to experience wage increases regardless of what firm they are in, sort into more productive firms, this pattern would also emerge. To gauge whether the pattern is actually driven by firms, I also estimate three AKM models separately for high-, mid-, and low-tenure workers. To illustrate why this helps asses whether the patterns are simply caused by sorting, Figure 3 and 4 highlight how the firm-tenure effects are identified by workers' moving patterns across different firms and tenure groups. In this example, Worker 1 starts as a low-tenure worker at Firm 1, stays and becomes high-tenure, then moves to Firm 2, where he starts as a low-tenure worker and eventually becomes a high-tenure worker. Worker 2 starts as low-tenure in Firm 1, switches to Firm 2 and eventually gets tenure. Finally, Worker 3, starts at Firm 1 and simply stays to achieve high tenure. When the AKM firm-tenure effects are estimated jointly, Worker 1 helps identify the difference between low and high tenure at both firms, Worker 2 helps identify the difference at Firm 2, and Worker 3 helps identify the difference at Firm 1. Additionally, Worker 1 and 2 help identify the difference in starting wages between Firm 1 and 2. When the firm-tenure effects are estimated separately, only workers who achieve the same tenure level at two different firms help identify the effects. Worker 1 helps identify the difference in low- and high-tenure effects between the two firms. Worker 2 only helps identify the difference in low-tenure effects, and Worker 3 provides no identifying variation. This approach essentially allows for both worker-specific and firm-specific returns to tenure, as opposed to a single worker effect.

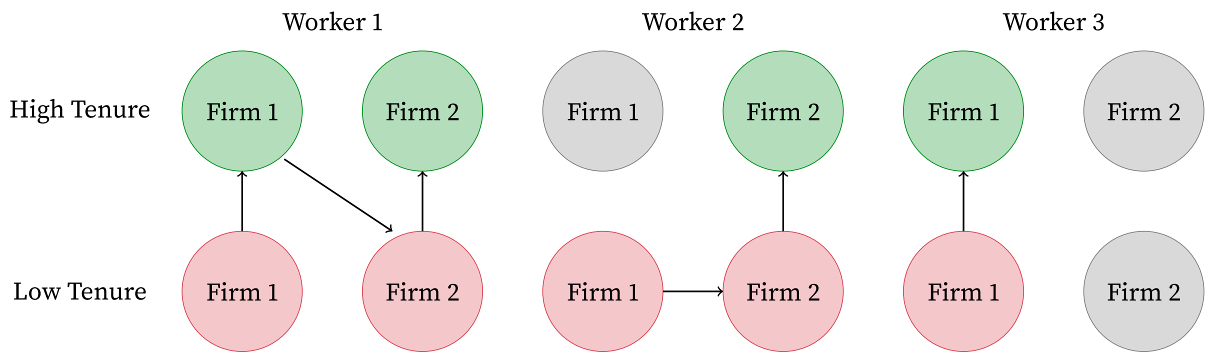


FIGURE 3. Identification of Firm-Tenure Effects when Jointly Estimated

Note: Visualization of how different worker tenure and firm-switching patterns help identify firm-tenure effects when effects are jointly estimated. Red circles indicates low-tenure effects identified by the worker pattern. Green indicate identified high-tenure effects. Grey indicate unidentified effects. Arrows indicate moves between firm-tenure cells, either from staying at a firm, or switching to another.

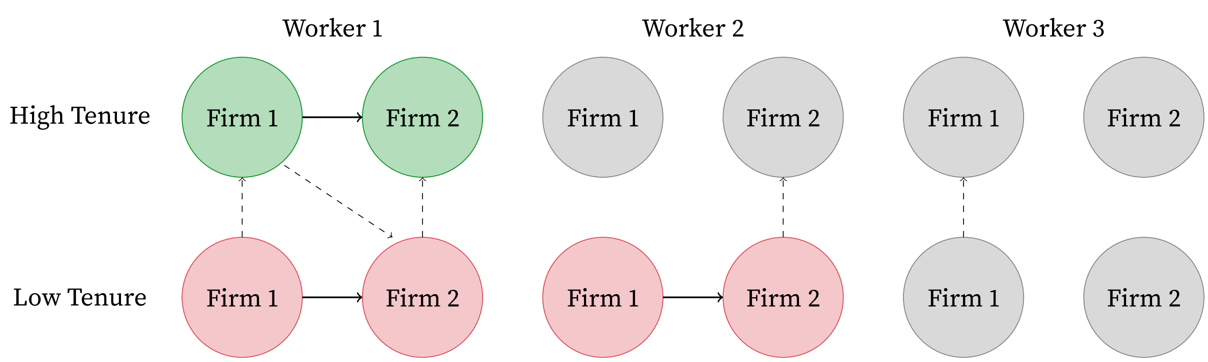


FIGURE 4. Identification of Firm-Tenure Effects when Separately Estimated

Note: Visualization of how different hypothetical tenure accumulation and firm-switching patterns help identify firm-tenure effects when effects are separately estimated. Red circles indicates low-tenure effects identified by the worker pattern. Green indicate identified high-tenure effects. Grey indicate unidentified effects. Arrows indicate moves between firm-tenure cells, either from staying at a firm, or switching to another. Dashed arrows indicates the actual movements, while the solid arrows indicate the implied movements in the two separate networks.

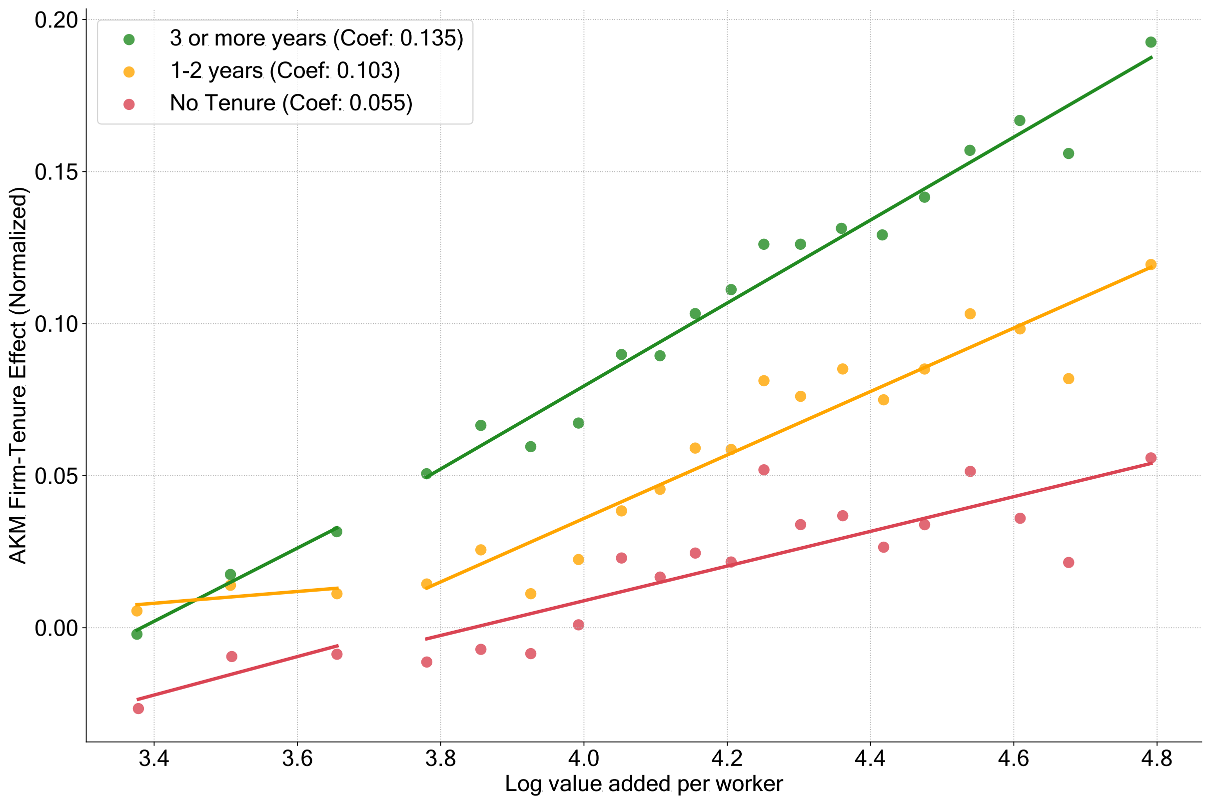


FIGURE 5. AKM Firm-Tenure FEs vs. Log value added per worker (Estimated Separately)

Note: This figure reports means of the estimated firm-tenure effects (ψ_{jk} in Eq. 1) by vingtiles of mean log value added per worker. Firm-tenure effects are estimated separately by tenure group. The estimated firm-tenure effects are normalized to have the same tenure-group mean as jointly estimated effects (Figure 2). The sample is described in Table D.2b. Projection slopes are obtained from regressing firm-tenure effects on log value added per worker in the microdata for firms with mean log value-added per worker above the kink (3.75). All statistics are weighted by average firm-size over sample period.

Figure 5 shows the estimated firm-tenure effects plotted against value added per worker, now using the separately estimated effects. Note, that the difference in intercept between the three tenure groups is not identified in the separate estimation and is normalized so that the mean firm-tenure effect in the different tenure categories is the same as in the pooled sample. The main takeaway is the striking similarity between Figure 2 and 5, with the differences in slopes between low and high tenure being 0.073 and 0.08 in Figure 2 and 5. This indicates that the heterogeneity in returns to tenure across firms is not just due to sorting on worker-specific returns to tenure.

The estimates of the firm-specific returns to tenure in Eq. 1 could also be biased if workers and firms select on match-specific returns to tenure. This would for example be the case if workers ex-ante could predict that they would learn particularly quickly at a firm compared to other workers, even if they were not quick learners in general. This is a general concern in AKM models, and to determine whether this is the case in the current setting, I probe for deviations from symmetry similarly to Card et al. (2016). If workers select into firms based on knowing the match-specific returns-to-tenure before the time of hire, we would expect workers who select into a firm to have higher returns than workers who select out of the same firm. This implies that the expected difference in returns to tenure when going from a firm that on average has high returns to one that on average has low returns will be different than the expected difference in returns for a worker moving in the other direction. In short, the difference in returns will be asymmetric, depending on the direction of the switch.

To test whether this is the case, I focus on workers who start at a firm with no tenure and achieve 3 years of tenure at two different firms in the sample period, job #1 and job #2, and calculate the individual returns to tenure for the worker at both firms. I also group firms into returns-to-tenure quartiles based on the estimated firm-tenure effects. If no selection is present the difference in returns to tenure between job #1 and job #2 if job #1 is at a bottom quartile firm and job #2 is at a top quartile firm, should be symmetric to the reverse case. If workers instead select positively on match-specific returns to tenure, we would expect the difference for moves in a "downward" direction to be smaller in size compared to those in an "upward" direction.

Figure 6 indicates that the changes are symmetric, and there is no indication of positive selection on the match-specific returns to tenure. All-in-all these results indicate that the estimated firm-tenure effects are not driven by sorting, but are truly firm-specific.

Industries, Institutions and Promotions: Figure 7 shows that the correlation between returns to tenure and productivity also is reflected in the differences across industries. Low-wage sectors that hire many workers without formal training, such as the Accommodation and the Food and Beverages service sector have low productivity and low returns to tenure while sectors with a high share of highly educated workers such as Accounting and Management Consultancy have high productivity and returns to tenure.

Figure 8 shows that industries with a higher degree of decentralized bargaining ex-

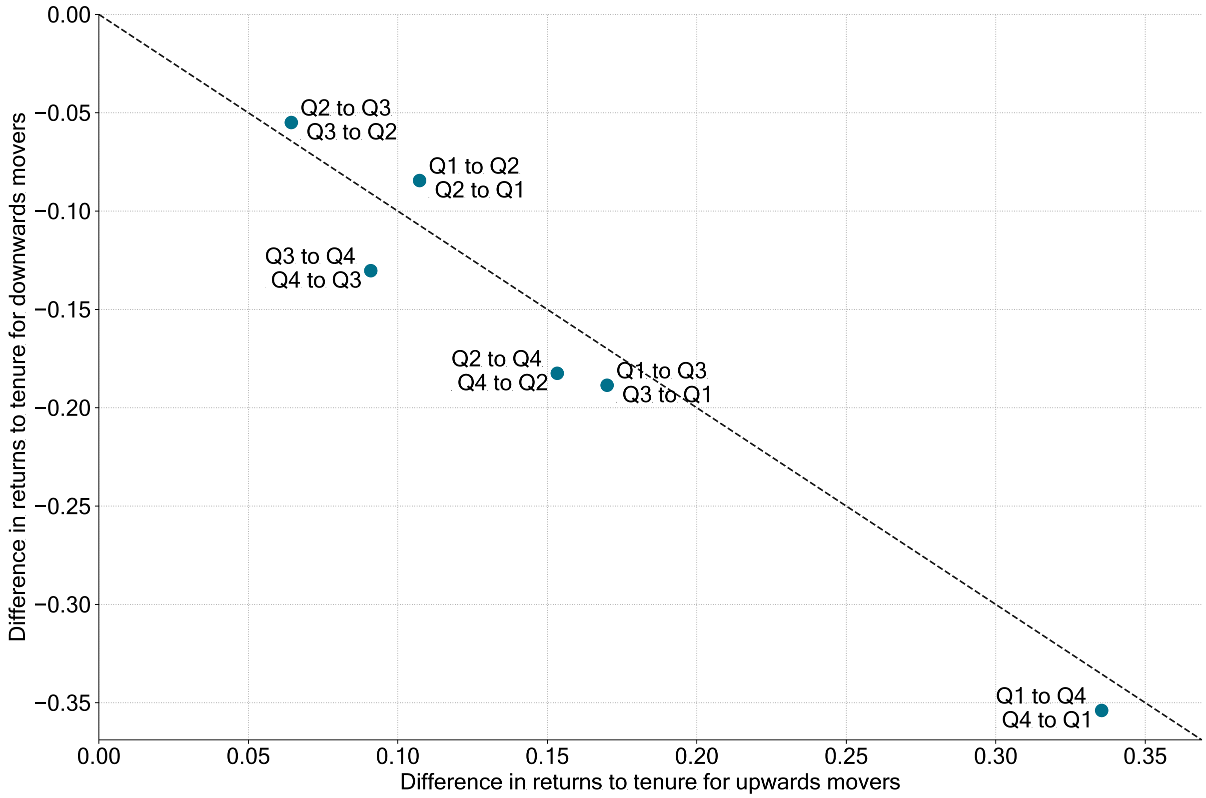


FIGURE 6. Test for symmetry of returns to tenure

Note: This figure reports differences in returns to tenure for workers who start with no tenure and achieves 3 years of tenure at two different firms in the sample period. The sample is described in Table D.1b. Individual returns are calculated as for Table 2. All firms are divided into quartiles based on the average returns to tenure. Each point represents workers who move between two returns-to-tenure quartiles. The x-axis reflect the mean difference in returns to tenure for workers who move upwards, e.g from a bottom quartile firm to a top quartile firm, and the y-axis reflects the mean difference in returns to tenure for workers who move downwards.

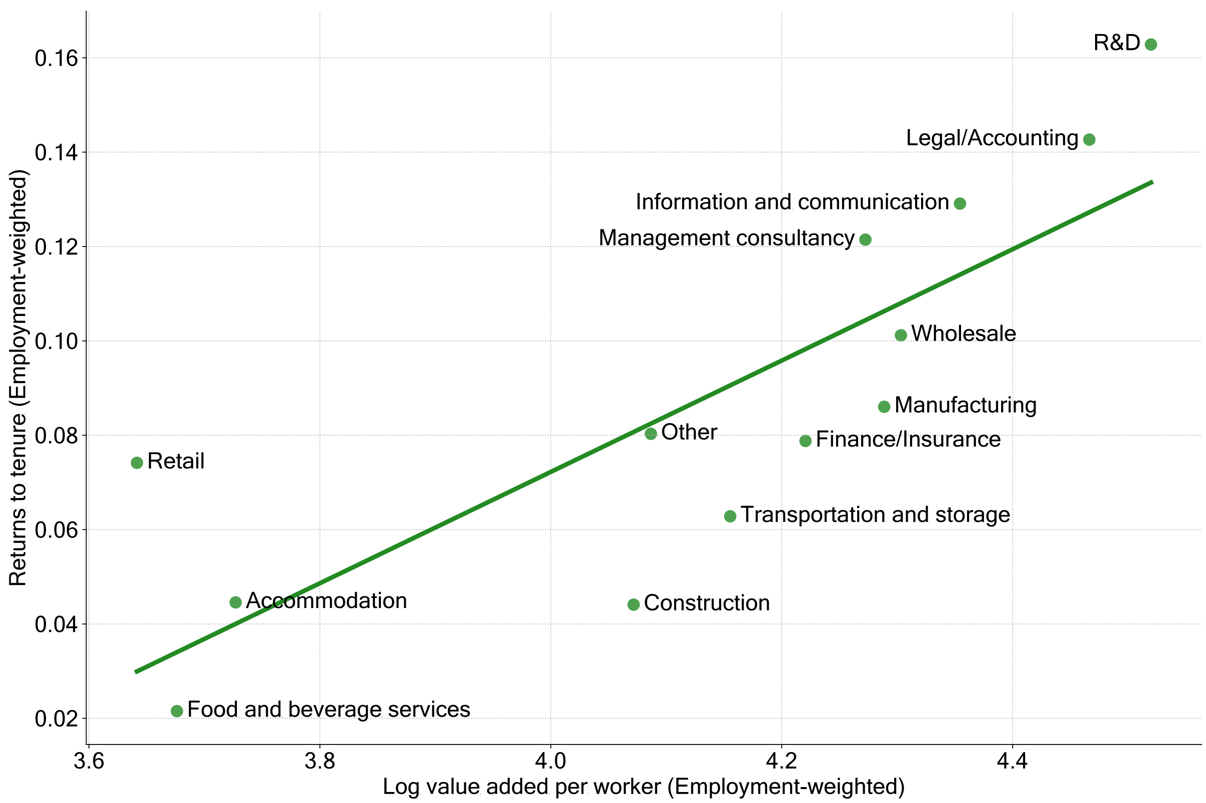


FIGURE 7. AKM Returns to Tenure vs. Log value added per worker by Industry

Note: This figure reports means of the estimated firm-tenure effects ($\psi_{jH} - \psi_{jL}$), where H and L indicates "3+ Years of Tenure" and "No Tenure", and mean log value added per worker for selected industries. The sample is described in Table D.1b. The slope is obtained from a regression using the industry means. All statistics are weighted by average firm-size over sample period.

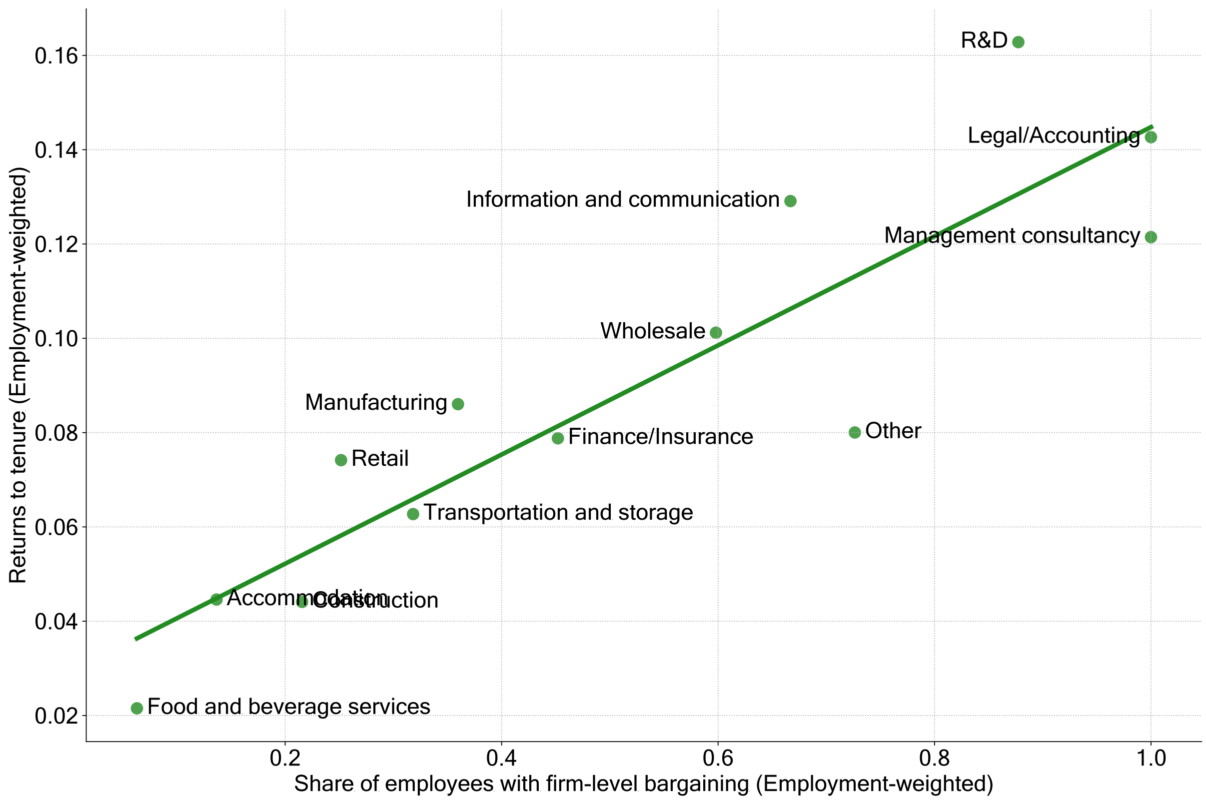


FIGURE 8. AKM Returns to Tenure and Centrality of Bargaining by Industry

Note: This figure reports means of the estimated firm-tenure effects ($\psi_{jH} - \psi_{jL}$) where H and L indicates "3+ Years of Tenure" and "No Tenure", and the share of employees covered by collective agreements with firm-level bargaining. This includes worker covered by Minimalløn and no wage restrictions as described in Section 2. The sample is described in Table D.1b. The slope is obtained from a regression using the industry means. All statistics are weighted by average firm-size over sample period.

hibit higher returns to tenure. This contrasts with the findings of Card et al. (2013), who report that firms with firm-level bargaining in Germany tend to have lower firm-specific wage premia.

One potential concern is whether the estimated returns to tenure are primarily driven by workers being promoted to managerial positions, which could complicate the interpretation of the estimated effects as salary increases for performing the same job. Figure B.3 addresses this by replicating Figure 2 using a sample that excludes all middle- and executive-level management employees. The results remain virtually unchanged.

4. How Portable are Returns to Tenure?

Having documented that the differences in returns to tenure and their relationship with productivity are indeed firm-specific, I now examine the long-term effects of these differences. Though the estimates from Section 3 reflect changes in hourly wages while workers remain at the firm, these returns may also influence the wage a worker receives after leaving a firm. For instance, if the differences in returns are driven by general human capital accumulation, these returns could be portable across firms. In this case, workers would retain some of the wage growth associated with tenure, even after changing employers.

To determine the degree to which the gains from tenure are portable I use the dual wage ladder (DWL) framework from Di Addario et al. (2023), which decomposes a worker's wage into a worker effect, a destination firm effect, and an origin firm effect. I extend the DWL model similarly to my extension of the AKM model, allowing the destination effect to vary by the employee's current tenure group and allowing the origin effect to vary by the tenure group when leaving the previous firm. The observed wage for worker i at time t is therefore decomposed as

$$y_{it} = x_{it}'\beta + \alpha_i + \psi_{\mathbf{j}(i,t)\mathbf{k}(i,t)} + \lambda_{\mathbf{h}(i,t)\mathbf{l}(i,t)} + \varepsilon_{i,t} \tag{2}$$

where $\mathbf{h}(i,t)$and $\mathbf{l}(i,t)$ are functions returning the identity of of the origin firm and maximum attained tenure-level at the origin firm of worker i in year t. λ_{hl} denotes the "origin" effect of having previously been employed at firm h with tenure-level l. If the match is the first job for the worker, the origin effect will default to a "No previous employment" effect. In practice this is also used as the normalizing origin effect.[9] In order to identify the destination and origin effects, I need to impose stronger restrictions than the network of firms being connected. As described in Di Addario et al. (2023) a number of requirements on the "destination" and "origin" networks need to be fulfilled jointly, for any effects to be identified. Additionally, a node in both networks needs to be chosen as the normalizing node. Finally, to estimate bias-corrected variance components, these restrictions need to hold when any single observation is dropped. To find the largest

[9] This differs from Di Addario et al. (2023) where all workers who separate involuntarily default to the same effect. In Section 5 I examine the relationship between portability and the type of separation. Note that the entire employment history from IDAN going back to 2000 is used to determine with a match is the first employment.

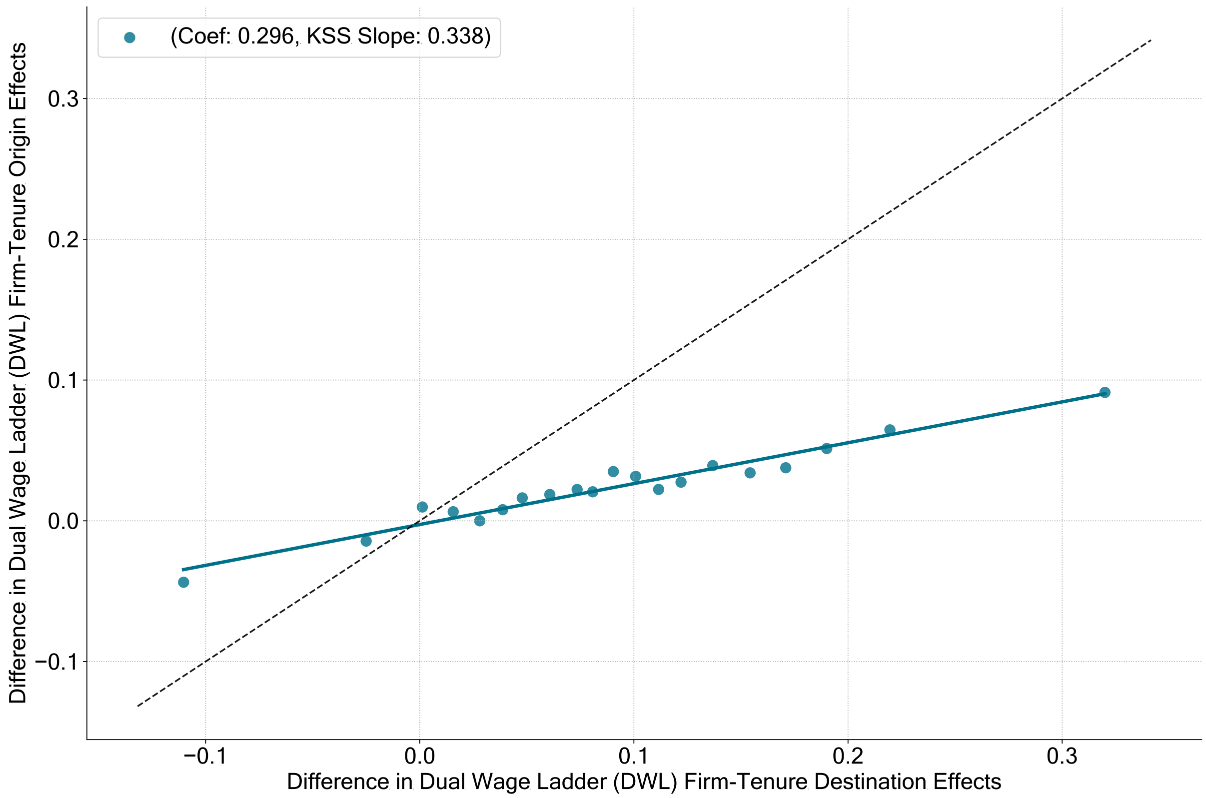


FIGURE 9. Dual Wage Ladder (DWL) Destination vs. Origin Returns to Tenure

Note: This figure reports means of the estimated firm-level differences in origin firm-tenure effects ($\lambda_{jH} - \lambda_{jL}$) by vingtiles of the estimated differences destination firm-tenure effects ($\psi_{jH} - \psi_{jL}$). The sample is described in Table D.3b. The projection slope is obtained from regressing estimated differences in origin firm-tenure effects on the estimated differences in destination firm-tenure effects in the microdata. KSS slope reports the bias-corrected slope as in Kline et al. (2020). All statistics are weighted by average firm size over the sample period.

identified networks I follow the computational procedures described by Di Addario et al. (2023). The resulting sample is described in Table D.3. Table C.4 reports the variance decomposition of log hourly wages based on the estimated effects.

Based on the estimates of the destination and origin firm-tenure effects from Eq. 2, it is possible to calculate two measures of returns to tenure. The first measure is the difference in destination firm-tenure effects $\psi_{jH} - \psi_{jL}$, where H and L indicate "3+ Years of Tenure" and "No Tenure". This is equivalent to the returns to tenure implied by the AKM effects from Figure 2, indicating the increase in wages a worker receives when they stay at a firm. The second measure is the difference in origin firm-tenure effects $\lambda_{jH} - \lambda_{jL}$. This indicates how much higher a worker's wage is at his current firm if he stayed for at least 3 years with their previous employer before leaving. It measures the portable part of the returns to tenure at a firm. Figure 9 plots total returns on the x-axis and portable returns at the same firm j on the y-axis.[10] The bias-corrected slope of 0.338 indicates that a third of the returns to tenure are portable.[11]

Additionally, Figure B.4 shows that the share of returns that are portable is stable across the productivity levels. In Table C.5 I examine whether the degree of portability depends on switching industries or occupations. The results indicate that portability is virtually unaffected by whether the job change involves an industry or occupation switch, which is consistent with the findings of Arellano-Bover and Saltiel (2024).

In addition to increasing the wage received at a given future employer, returns to tenure can also increase future wages by driving the selection of who the future employer is. Table C.6 shows that high-tenure workers at firms with greater returns to tenure are more likely to transition to firms that offer higher starting wages, as measured by the estimated firm-tenure effects. Whether this phenomenon arises from higher reservation wages or if high-wage firms preferentially select workers who have accumulated more human capital remains an open question for future research.

5. Mechanisms: Portable Returns to Tenure

Having documented that differences in the returns to tenure and their relationship with productivity are innate to the firms, I now turn to exploring the potential mechanisms behind this phenomenon. I begin by investigating the factors that drive the portable component of returns.

General Human Capital: A common explanation for the returns to tenure is the accumulation of human capital (Becker 1962), which may vary in its rate across firms (Gregory 2023; Arellano-Bover and Saltiel 2024). If more productive firms provide better learning environments, this could explain the observed patterns. This includes both *general* human capital, which improves a worker's productivity across all firms, and *firm-specific* human capital which only increases productivity at the current firm. Differences in

[10] Note that this is for the same firm (j) and not the observed destination-origin pairs (j, h).

[11] The bias-correction is performed as in Kline et al. (2020).

general human capital accumulation could also explain why a portion of the returns to tenure is portable.

However, the fact that a third of returns are portable does not necessarily imply that a third of the heterogeneity in returns to tenure is driven by general human capital accumulation. Factors that only affect worker behavior and productivity at their previous firm can also appear portable if firms compete for workers through poaching and counteroffers (Lazear 2009). For instance, firms would need to bid higher to poach from firms where workers gain firm-specific human capital quickly, even though they would not be more productive at the new firm.

To assess whether the portability of returns is driven by general human capital accumulation, I examine whether returns to tenure remain portable when workers are involuntarily separated from their employer. Such separations reset workers' bargaining positions. I estimate a new dual wage ladder model, allowing the origin firm-tenure effects to vary depending on whether the worker transitions between the firms through an Employment-to-Employment transition (EE) or Employment-to-Unemployment-to-Employment transition (EUE). A transition is labeled as EUE if a worker receives unemployment insurance benefits within 21 days of their last day of employment at the origin firm. This criterion ensures that separations are involuntary as workers who quit their jobs are disqualified from unemployment insurance benefits for the first 21 days following a separation according to Danish unemployment insurance regulations.

Figure 10 shows that nearly a third of the total returns to tenure and over 90% of the portable portion are retained even after an involuntary separation. This suggests that the majority of the portable returns to tenure arise from differences in the accumulation of general human capital across firms.

Poaching and Sequential Auction Models: A worker's previous employer can influence not only the wage level at the current employer but also the returns to tenure, particularly if firms compete for labor through offers and counter-offers to poach workers, as described in Postel–Vinay and Robin (2002). In this model, the poaching and incumbent firms engage in a sequential auction for the worker. The most productive firm wins by offering a wage that matches the total surplus of the match for the losing firm. A high-tenure worker at a low-productivity firm will not have received many wage-increasing

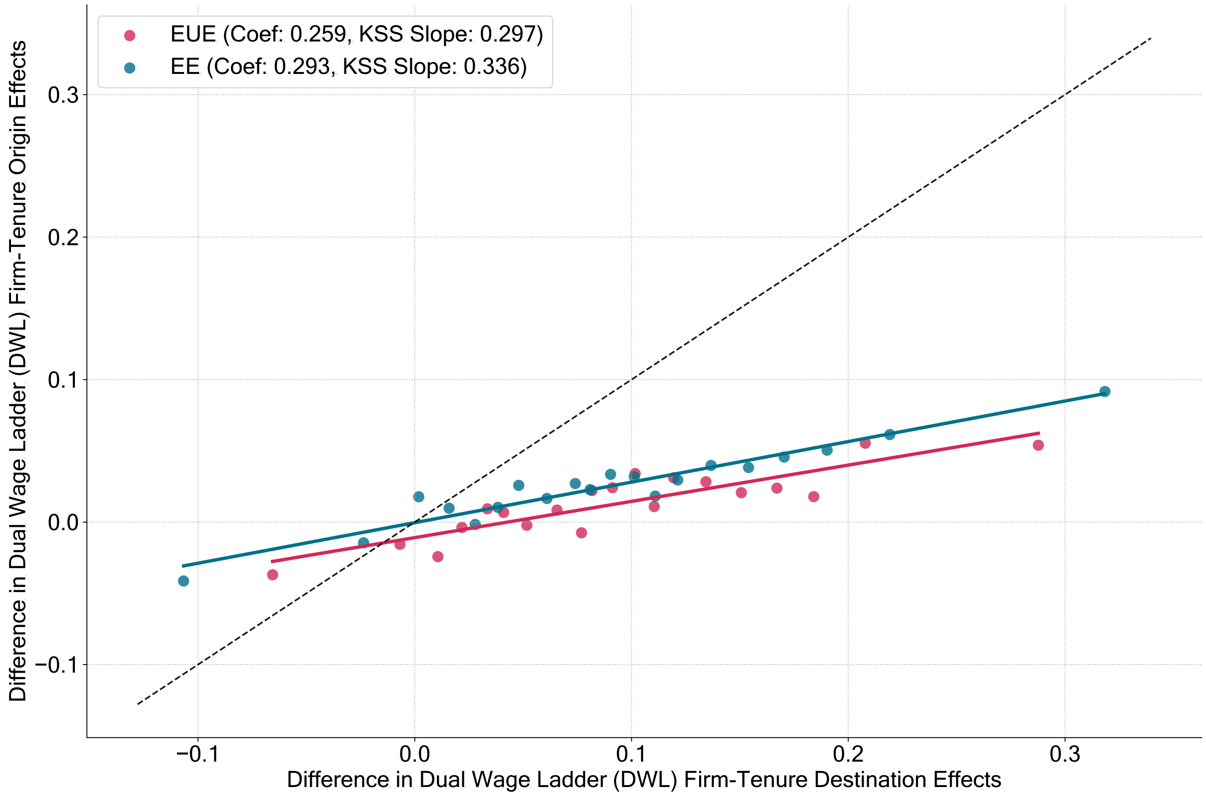


FIGURE 10. Dual Wage Ladder (DWL) Destination vs. Origin Returns by Separation Type

Note: This figure reports means of the estimated firm-level differences in origin firm-tenure effects ($\lambda_{jH} - \lambda_{jL}$) by vingtiles of the estimated differences destination firm-tenure effects ($\psi_{jH} - \psi_{jL}$) and by separation type. The sample is described in Table D.4b. The projection slopes is obtained from regressing estimated differences in origin firm-tenure effects on the estimated differences in destination firm-tenure effects in the microdata. KSS slope reports the bias-corrected slope as in Kline et al. (2020). All statistics are weighted by average firm size over the sample period.

offers, because the incumbent firm would have lost the bidding and the worker would have left. In contrast, a high-tenure worker at a productive firm might have received many wage-increasing offers that did not result in leaving the firm. This would lead to more productive firms having higher returns to tenure as seen in Section 3. Furthermore, I will demonstrate that this type of model implies that a worker's previous employer directly affects the returns to tenure at their current employer.

To assess the importance of this type of competition, I examine the relationship between the returns to tenure experienced by a worker at a new employer and the productivity of the previous employer from which they were poached. In Postel–Vinay and Robin (2002) the wage of a new hire who has just been poached from another firm is given by

$$\ln \phi(\epsilon, p, q) = \ln \epsilon + \ln q - \kappa \int_q^p \frac{\bar{F}(x)}{x} dx \tag{3}$$

where ϵ represents the time-constant productivity of the worker, q denotes the productivity of the previous employer, p is the productivity of the current employer, $1 - \bar{F}(x)$ is the cumulative distribution function of the productivity distribution of firms that workers encounter and κ function of the offer arrival rate, the discount rate and the exogenous separation rate. As noted by Di Addario et al. (2023) this can also be written as

$$\ln \phi(\epsilon, p, q) = \ln \epsilon + I(p) + \ln q - I(q) \tag{4}$$

where $I(z) = \kappa \int_z^\infty \frac{\bar{F}(x)}{x} dx$. As time goes on, a worker will receive offers from other firms, that might either cause them to leave or receive a raise. In the latter case, the wage will given by $\ln \phi(\epsilon, p, x)$ where x is the productivity of the most productive firm that has tried to poach the worker. In Appendix E I show that the expected returns to tenure conditional on not being poached are given by

$$E\left(\Delta \ln \phi_\tau\left(\varepsilon, p, q\right)\right) = \frac{1}{M_\tau(p)} \int_q^p \left((\ln x - I(x)) - (\ln q - I(q))\right) dM_\tau(x) \tag{5}$$

where M_τ is the cdf. for the maximum draw from F(x), in a interval of length τ. The expected returns to tenure depend positively on the productivity of the current employer, p, and negatively on the productivity of the previous employer, q, through two channels. First, the higher q is, the lower the probability that a given encounter will result in a raise. This is captured by q being the lower limit of the integral. Second, conditional on receiving a raise, the size of the raise will be smaller the higher q is, since $(\ln q - I(q))$ is increasing in q. Therefore, this type of sequential auction model predicts that returns to tenure should decrease with the productivity of a worker's previous employer.[12]

In Table 3, I test this prediction by regressing individual worker-firm returns to tenure on the log value added per worker of the worker's previous employer. All specifications indicate that individual returns to tenure are increasing in the productivity

[12] In Appendix E, I show that this is still the case when the model is extended to include bargaining and returns to experience as in Bagger et al. (2014).

TABLE 3. Previous Firm Productivity and Individual Returns to tenure

	(1)	(2)	(3)
Constant	-0.050***	-0.237***	
	(0.019)	(0.029)	
Previous Firm Productivity	0.031***	0.006	0.007**
	(0.005)	(0.005)	(0.003)
Current Firm Productivity		0.069***	
		(0.005)	
Current Firm Productivity Percentile FE	No	No	Yes
No. of Observations	189,011	189,011	189,011

Note: This table reports the coefficients obtained from projecting individual worker-firm returns to tenure on the productivity of a worker's current and previous employer. Individual returns are calculated as for Table 2. The sample is described in Table D.1b. Mean Log value-added per worker is used as the measure for firm-level productivity. "Current Firm Productivity Percentile FE" indicates the inclusion of dummy controls indicating the firm-size weighted productivity percentile of the current firm. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of the previous employer. When I control for the productivity of the current employer, the coefficients are small and economically irrelevant. This directly contradicts Eq. 5 and suggests that the estimated firm-tenure effects are unlikely to be driven by firms attempting to poach workers from competing firms, with productive firms countering more offers.

6. Mechanisms: Non-Portable Returns to Tenure

I now examine potential mechanisms driving the non-portable heterogeneity in returns to tenure. Various theories explain the observed patterns, including firm-specific human capital accumulation (Becker 1962; Lazear 2009), differential learning about match quality (Jovanovic 1979; Moscarini 2005), and varying use of wage-tenure contracts (Lazear 1979; Burdett and Coles 2003; Stevens 2004).

However, these theories are difficult to distinguish based on wage growth alone. To address this, I follow the strategy of Nagypál (2007), which uses worker mobility to distinguish between firm-specific human capital accumulation and learning about the match quality. Both cases predict rising wages and decreasing separations with tenure. The key difference lies in how negative shocks affect separations across different tenure groups.

In the case of firm-specific human capital accumulation, the worker's productivity and the match surplus increase with tenure. As a result, low-tenure workers are more likely to be laid off during a downturn compared to their more productive high-tenure colleagues.

In contrast, under the learning-about-match-quality framework, the match surplus does not necessarily increase with tenure even though expected productivity does, because the option value of a match will decrease over time: The potential upside for a new worker is unrestricted, while the potential downside is limited by the ability to separate if the match proves poor. As uncertainty about the match quality diminishes, the potential gain falls more than the potential loss. As a result, low-tenure matches may have a higher continuation value than high-tenure ones with the same expected productivity. Nagypál (2007) shows that this implies a negative shock can cause a proportional increase in separation rates across the tenure spectrum and may even reduce the gap in separation rates across tenure groups. Nagypál (2007) ultimately finds that average returns to tenure are primarily driven by learning about match quality.

I apply the same intuition to identify the drivers of heterogeneity in returns to tenure. If separations are bilaterally efficient, differences in firm-specific human capital accumulation imply that after a negative shock, the change in the gap in separation rates between tenure groups should be *higher* at firms with large returns to tenure, since the productivity differences between high- and low-tenure workers will be larger.

Conversely, if firms are learning about match quality, differences in the returns to tenure will either be due to firms observing a less noisy signal or the ex-ante variation in the quality of matches being higher. In both cases, the option value of new hires will be high at firms with large returns. In the first case, the time before a bad match separates is reduced, lowering the potential loss. In the second case, the potential gain increases more than the loss, since the loss is limited by the option to separate. Both imply that the change in the gap in separation rates between tenure groups should be *lower* at firms with large returns to tenure.

The last candidate theory considered in the paper is that productive firms more often use wage-tenure contracts as in Burdett and Coles (2003). In this setting, firms post contracts that offer increasing wage-tenure schedules. This allows firms to attract and retain workers, while initially paying them lower wages than they would otherwise have to. In this case, the total surplus does not change with tenure, only the division. The change in tenure gap in separation rates should, therefore, be *uncorrelated* with the returns to tenure at a firm.

To test these predictions empirically, I follow Nagypál (2007) and use negative net changes in firm-level employment, denoted as $\Delta e_{j,t}$, as a proxy for negative shocks to firms. I then regress the gap in the separation rates between the "No Tenure" and "3+ Years of Tenure" groups, $\hat{s}_{j,t} = s_{j,t,L} - s_{j,t,H}$, on $\Delta e_{j,t}$, allowing slope to depend on the estimated returns to tenure at the firm, $\psi_{jH} - \psi_{jL}$. Specifically, the regression model is:

$$\hat{s}_{j,t} = \beta_0 + \beta_1 \Delta e_{j,t} + \beta_2(\psi_{jH} - \psi_{jL}) + \beta_3(\psi_{jH} - \psi_{jL}) e_{j,t} + \varepsilon_{j,t} \tag{6}$$

Alternatively, I allow slope to vary by quartiles of returns to tenure. The sample is restricted to firm-year observations with negative net employment changes.

The results are shown in Table 4. The estimates indicate that the change in the separation rate gap between tenure groups in response to a negative shock is *smaller* at firms with higher returns to tenure.[13] This is in line with the predictions of the

[13]Note "Empl. Net Change" is always negative.

learning-about-match-quality framework and is consistent with the findings in Nagypál (2007). Unlike the analysis of portable returns in Section 5, it is challenging to quantify the relative importance of different drivers. However, the results suggest that the most important driver of the non-portable part of the returns to tenure is workers and firms learning about match quality.

TABLE 4. Tenure-Gap in Separation Rates by Employment Net Change

	(1)	(2)	(3)	(4)	(5)
Constant	0.111***	0.130***	0.150***		0.338***
	(0.007)	(0.009)	(0.009)		(0.069)
Returns to Tenure (AKM)		-0.190***			
		(0.062)			
Empl. Net Change	-0.195***	-0.247***	-0.356***	-0.354***	-0.982***
	(0.023)	(0.027)	(0.049)	(0.051)	(0.272)
Empl. Net Change × Returns to Tenure (AKM)		0.828***			
		(0.196)			
Returns to Tenure (AKM) Q2			-0.029**	-0.027**	
			(0.013)	(0.013)	
Returns to Tenure (AKM) Q3			-0.030*	-0.045***	
			(0.017)	(0.012)	
Returns to Tenure (AKM) Q4			-0.065***	-0.069***	
			(0.011)	(0.013)	
Empl. Net Change × Returns to Tenure (AKM) Q2			0.095	0.092	
			(0.068)	(0.066)	
Empl. Net Change × Returns to Tenure (AKM) Q3			0.228***	0.221***	
			(0.062)	(0.063)	
Empl. Net Change × Returns to Tenure (AKM) Q4			0.283***	0.271***	
			(0.064)	(0.065)	
Log Value Added Per Worker					-0.054***
					(0.015)
Empl. Net Change × Log Value Added Per Worker					0.197***
					(0.066)
Starting Wage AKM Percentile FE	No	No	No	Yes	No
No. of Observations	70,639	70,639	70,639	70,639	70,639

Note: This table reports the coefficients obtained from projecting the difference in separation rates at firm-year level, $\hat{s}_{j,t} = s_{j,t,L} - s_{j,t,H}$, on the firm-level employment net change in pct., $\Delta e_{j,t}$, weighted by the average firm-size over the sample period (Eq 6). The sample is described in Table D.1b, but is further restricted to firm-year observations with negative net employment changes. $Q2 - Q4$ denotes the quartiles of estimated returns to tenure, $\psi_{jH} - \psi_{jL}$ from Eq. 1. "Starting Wage AKM Percentile FE" indicates the inclusion of dummy controls indicating firm-size weighted percentile for the estimated "No Tenure" AKM firm-tenure effect. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7. Cost of Job Displacements and Returns to Tenure

It is well-documented that tenure and the cost of job loss are connected (Topel 1991; Jacobson et al. 1993). Having established heterogeneity in firm-specific returns to tenure, it follows directly that these differences might also drive variations in the cost of job loss. This, in turn, has implications for policies aimed at reducing the cost of job loss or preventing job loss altogether, such as short-time working schemes, which, for example, were employed in the U.S. during the COVID-19 pandemic (Cahuc 2024). Autor et al. (2022) evaluates the effectiveness of these types of programs by estimating the cost per job saved. However, this is not the only relevant dimension when assessing the efficiency of such programs. If the value of matches varies, it would arguably be more beneficial to preserve high-value matches, if we disregard redistribution concerns. For instance, some jobs may require years of training and screening, making them more valuable to retain. In terms of earnings losses, if a worker can quickly secure a new position with comparable pay following the loss of a match, the value of preserving the original match is lower.

To evaluate how the cost of job loss varies with firm-specific returns to tenure, I follow the mass-layoff literature. Following Lachowska et al. (2020) and Bertheau et al. (2023), I define a mass-layoff event as a drop in firm-level employment of at least 30% at a firm with at least 50 employees prior to the event, with the year of the event denoted as t^*. A worker is categorized as displaced if he separates in the same year as a mass-layoff event. Similarly to Bertheau et al. (2023), I construct a control group by matching each displaced worker with a non-displaced worker, strictly matching on year, gender, and industry. Within each year-gender-industry cell, I then estimate a propensity score model for the likelihood of being displaced. The model includes earnings measured in $t^\star - 2$ and $t^\star - 3$, age, tenure, and employer size in $t^\star - 1$. I use a 1:1 nearest-neighbor matching algorithm to assign one control worker to each treated worker based on the estimated propensity scores.

Since the identifying variation for the estimated firm-tenure effects comes from switches between firms, including those triggered by mass layoffs, using these observations in the estimation of earnings losses would lead to bias. To prevent this, I estimate new firm-tenure effects using a sample that excludes all workers who are either displaced or matched controls.

In line with Bertheau et al. (2023), I restrict the sample to workers who have stayed at the same firm from $t^* - 3$ to t^*. Similarly to Lachowska et al. (2020), I restrict the sample to workers for whom I observe earnings in all years from $t^* - 3$ to $t^* + 3$. The estimates should, therefore, be interpreted as the effects of displacement on workers who remain attached to the labor force. To estimate the earnings loss due to displacement, I use the following event study model:

$$
\begin{aligned}
y_{it} &= \alpha_i + \lambda_t + \sum_{h=-3}^{h=3} \gamma_{h\mathbf{q}(i)} \mathbf{1}\{t = t_i^* + k\} + \sum_{h=-3}^{h=3} \theta_{h\mathbf{q}(i)} \mathbf{1}\{t = t_i^* + k\} \times \text{Displaced}_i \\
&+ \sum_{h=-3}^{h=3} \rho_h \mathbf{1}\{t = t_i^* + k\} \psi_{\mathbf{j}(i,t_i^*)L} + \sum_{h=-3}^{h=3} \phi_h \mathbf{1}\{t = t_i^* + k\} \times \text{Displaced}_i \times \psi_{\mathbf{j}(i,t_i^*)L} + X_{it}' \beta + r_{it}
\end{aligned}
\tag{7}
$$

where $\mathbf{q}(i)$ is a function that matches a worker to the firm-specific returns quartile, i.e. quartiles of $\psi_{jH} - \psi_{jL}$. The outcome variable, y_{it}, is the total yearly real log earnings across all jobs. α_i represents a worker fixed effect, and λ_t is a calendar-year fixed effect. Assuming parallel trends between treated and control units, the coefficients of interest, $\theta_{h\mathbf{q}(i)}$, capture the causal effect of job loss at event time k. The coefficients $\theta_{h\mathbf{q}(i)}$ are normalized relative to the coefficient at $t^* - 3$. I estimate these coefficients using OLS. Note that I demean $\psi_{\mathbf{j}(i,t^*i)L}$ before including it in the regression, so $\theta_{h\mathbf{q}(i)}$ should be interpreted as the change in earnings for workers displaced from a firm with an average firm-specific starting wage and returns to tenure in the qth quartile. Standard errors are clustered at the worker level.

The results are shown in Figure 11. Being displaced is generally associated with substantial earnings losses, but the magnitude strongly depends on the firm-specific returns to tenure of the firm from which workers are displaced. Workers with high tenure who are displaced from a firm in the top quartile of returns experience an earnings loss that is 80 % higher in the first year after displacement compared to workers displaced from firms in the lowest quartiles. After three years, the earnings loss for workers from low-returns firms is reduced to 0.03 log points, while for those displaced from firms in the top returns quartile, the loss only drops to 0.1 log points. The difference in earnings losses is statistically significant at all post-displacement time horizons.

These results indicate that firm-specific returns to tenure are an important driver of heterogeneity in the cost of job loss. Policymakers designing policies to mitigate these losses should take this fact into account.

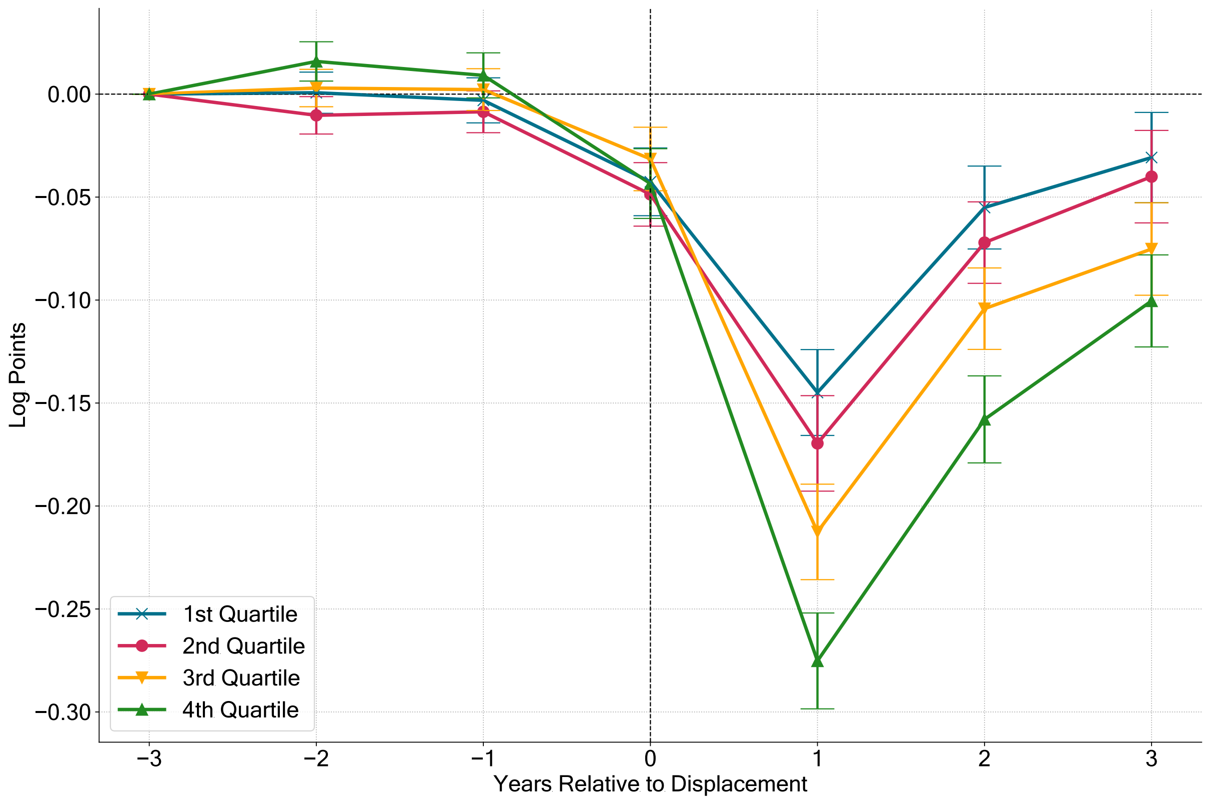


FIGURE 11. Estimated displacement losses by Firm-specific Returns to Tenure

Note: This figure reports the estimated log year earnings lost due to displacement by quartiles of firm-specific returns to tenure of the displacing firm, i $\psi_{jH} - \psi_{jL}$, while also allowing the effects to depend on firm-specific starting wages, ψ_{jL}. The firm-tenure effects are estimated using a sample that excludes all workers used for estimating loses. Whiskers denote 95 percent confidence intervals based on standard errors clustered by worker.

8. Conclusion

The positive relationships between wages and tenure and wages and firm-level productivity are well-established. The results of this paper indicate that these regularities are also connected: A large part of the positive correlation between wages and productivity comes from higher returns to tenure in the cross-section. A key finding is that these differences in the returns to tenure across firms are not simply due to composition effects or "quick learners" sorting into productive firms but instead reflect the truly firm-specific characteristics.

I also show that these differences have long-term effects: A third of the gains from tenure are portable when switching employers. This remains true even when workers separate involuntarily, indicating that these gains reflect heterogeneity across firms in general human capital accumulation. The gains are not driven by more productive firms being able to counter more poaching offers from competing firms. Additionally, I present suggestive evidence that the non-portable portion of returns is primarily driven by variations in how workers and firms learn about the quality of their match over time.

Finally, I show that firm-specific returns significantly influence the cost of job loss. Real earnings losses from displacement during a mass-layoff are nearly twice as large for workers displaced from firms in the top quartile of the returns distribution compared to those from the bottom quartile.

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Appendix A. Data Sources

Table A.1 contains information on the individual data sources used in this paper.

TABLE A.1. Summary of the Data Sources

Data set	Source	Period	Main Variables
Detaljeret lønmodtagerdata fra e-Indkomst (BFL)	DST	2010-2019	Employer, Wages
IDA persondata (IDAP)	DST	2010-2020	Workforce characteristics
IDA persondata (IDAN)	DST	2000-2020	Pre-BFL work history
Generel firmastatistik (FIRM)	DST	2010-2020	Value added, Revenue, Industry
Befolkningen (BEF)	DST	2010-2020	Demographics
OK-forhandlingsniveauer	DA	2019	Centrality level of wage bagaining

Note: The table reports the data sets used. The data sets come from Statistics Denmark (DST, *Danmarks Statistik*) and the Danish Employers Association (DA, *Dansk Arbejdsgiverforening*).

Appendix B. Additional Figures

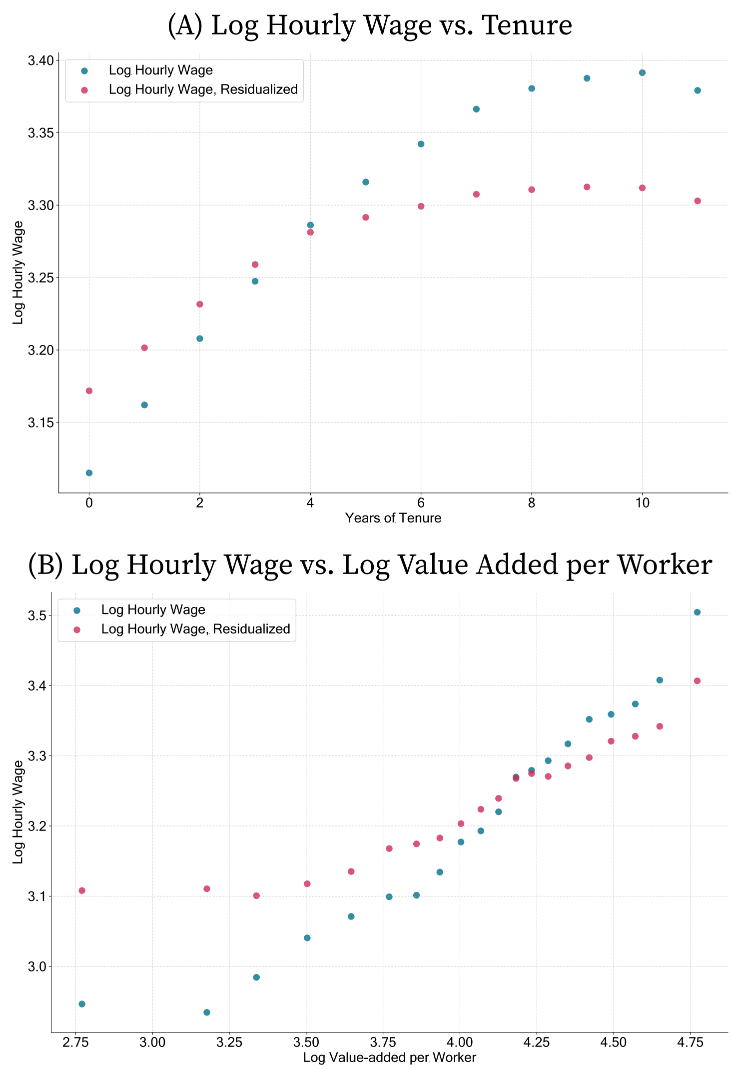
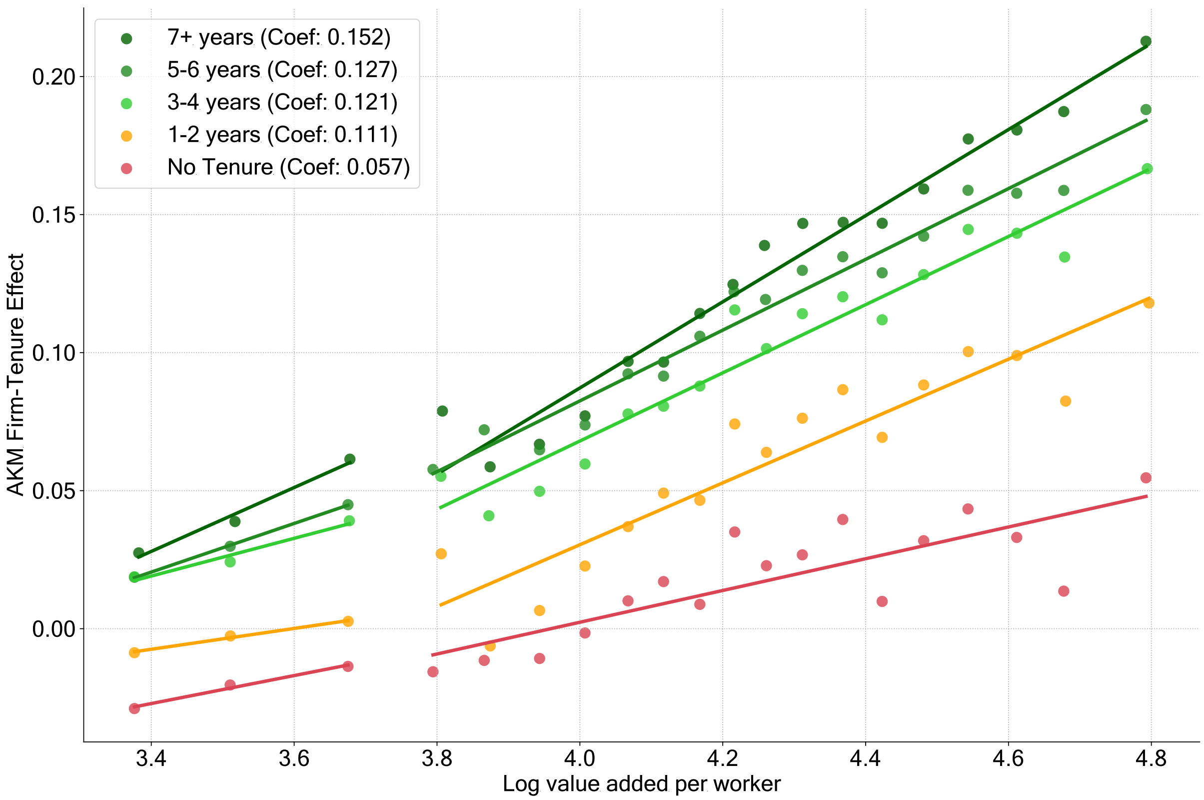


FIGURE B.1. Wages, Tenure and Productivity

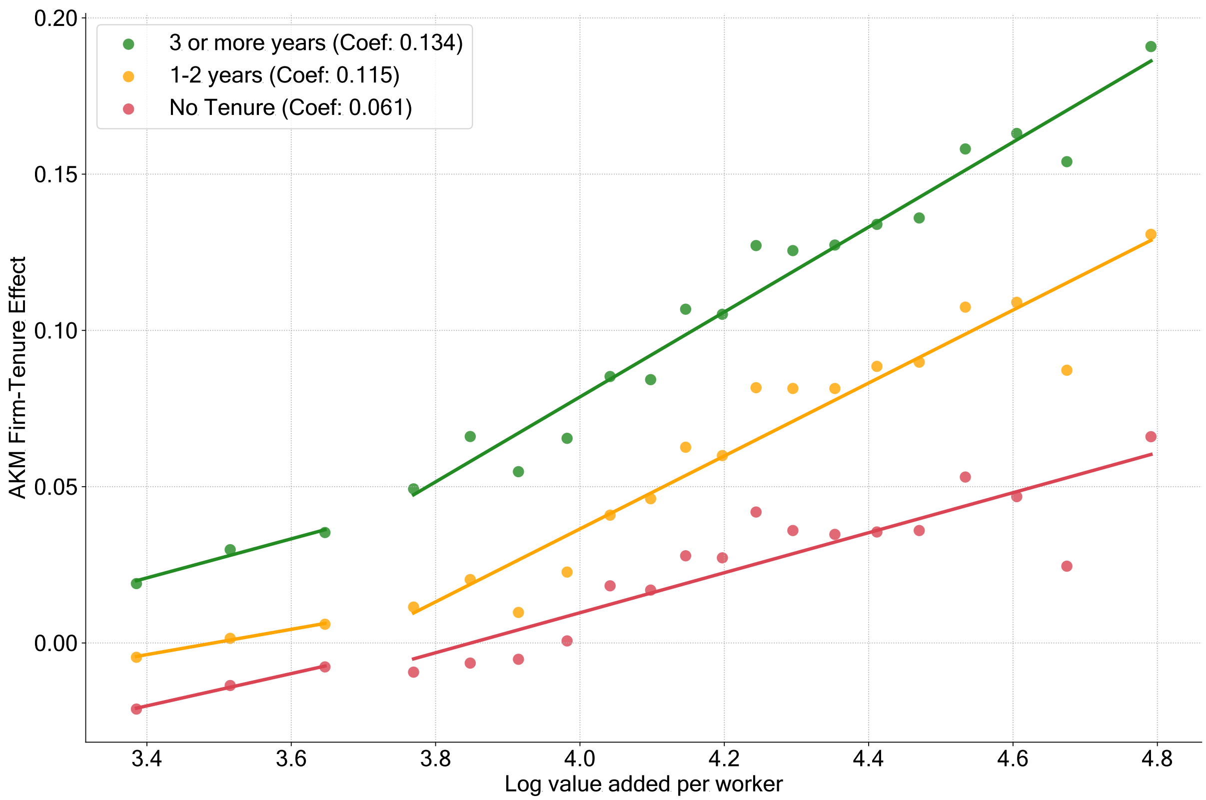
Note: Panel (a) reports means mean log hourly wage at each observed year of tenure. Panel (b) reports means of log hourly wage by vingtiles of mean log value added per worker. Residualized log hourly wages are residualized via an OLS regression including including education-specific year dummies and education-specific cubic polynomials in age. The sample is described in Table D.1b.

FIGURE B.2. AKM Firm-Tenure FEs vs. Log value added per worker (5 Tenure Categories)



Note: This figure reports means of the estimated firm-tenure effects (ψ_{jk}) by vingtiles of mean log value added per worker using 5 tenure groups instead of 3. Firm-tenure effects are estimated jointly in a pooled sample. The sample is described in Table D.1b, but is further to firms for which all 5 tenure groups are identified. Projection slopes are obtained from regressing firm-tenure effects on log value added per worker in the microdata for firms with mean log value-added per worker above the kink (3.75). All statistics are weighted by average firm-size over sample period.

FIGURE B.3. AKM Firm-Tenure FEs vs. Log value added per worker Excluding Managers



Note: This figure reports means of the estimated firm-tenure effects (ψ_{jk}) by vingtiles of mean log value added per worker, excluding all observations of workers in upper and middle management positions based on ISCO-occupation codes. Firm-tenure effects are estimated jointly in a pooled sample. The sample is described in Table D.1b, but is further to restricted to exclude person-year observation in managerial occupations. Projection slopes are obtained from regressing firm-tenure effects on log value added per worker in the microdata for firms with mean log value-added per worker above the kink (3.75). All statistics are weighted by average firm-size over sample period.

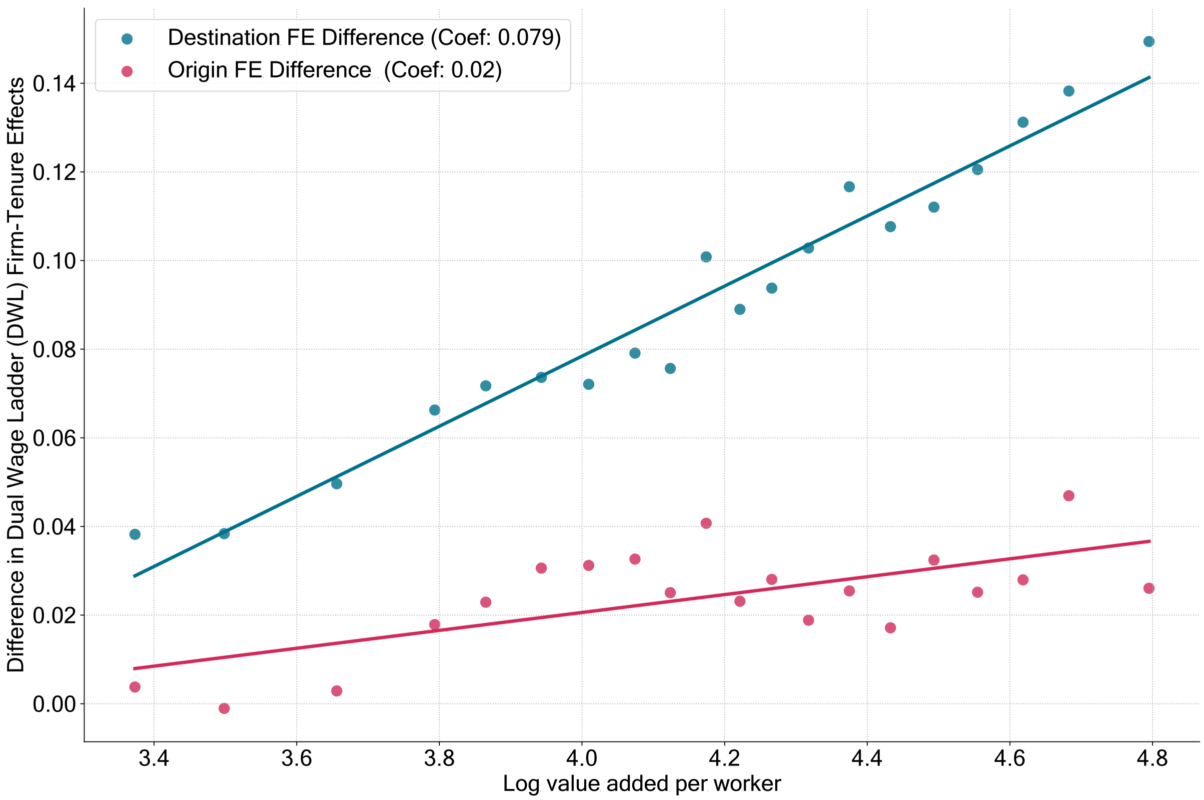


FIGURE B.4. Dual Wage Ladder (DWL) Returns to Tenure vs. Value Added

Note: This figure reports means of the estimated firm-level differences in destination and origin firm-tenure effects ($\psi_{jH} - \psi_{jL}$ and $\lambda_{jH} - \lambda_{jL}$) by vingtiles of mean log value added per worker. The sample is described in Table D.3b. Projection slopes are obtained from regressing the differences on log value added per worker in the microdata. All statistics are weighted by average firm-size over sample period.

Appendix C. Additional Tables

TABLE C.1. Firm-Tenure Effects and Value-Added - Additional Controls

	(1)	(2)	(3)	(4)
	Firm FE	Firm-Tenure FE	Firm FE	Firm-Tenure FE
Constant	-0.345***	-0.416***	-0.362***	-0.406***
	(0.042)	(0.042)	(0.039)	(0.042)
No Tenure		0.181***		0.107***
		(0.027)		(0.028)
3+ Years of Tenure		-0.038***		-0.032**
		(0.014)		(0.015)
Log Value Added per Worker	0.105***	0.114***	0.116***	0.119***
	(0.010)	(0.010)	(0.009)	(0.010)
No Tenure X Log Value Added per Worker		-0.052***		-0.036***
		(0.006)		(0.006)
3+ Years of Tenure X Log Value Added per Worker		0.020***		0.016***
		(0.003)		(0.003)
Tenure Group × Industry FE (Nace 1d)	No	No	Yes	Yes
No. of Observations	38,436	125,718	38,436	125,718

Note: This table reports the coefficients obtained from projecting the estimated firm-tenure effects from Eq. 1 on firm-level mean log value-added. The sample is described in Table D.1b, but is further to restricted to only include firms with mean log value added per worker above 3.75 indicated by the kink in Figure 2. The regression is weighted by firm-size averaged over the sample period Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.2. Firm-Tenure Effects and Firm Characteristics

	(1)	(2)	(3)	(4)
	Firm FE	Firm-Tenure FE	Firm FE	Firm-Tenure FE
Constant	-0.342***	-0.417***	-0.012***	-0.045***
	(0.042)	(0.038)	(0.002)	(0.002)
No Tenure		0.186***		0.001
		(0.022)		(0.001)
3+ Years of Tenure		-0.036***		0.029***
		(0.013)		(0.002)
Log Value Added per Worker	0.104***	0.114***		
	(0.010)	(0.009)		
No Tenure × Log Value Added per Worker		-0.053***		
		(0.005)		
3+ Years of Tenure × Log Value Added per Worker		0.020***		
		(0.003)		
Log Firm Size			0.027***	0.027***
			(0.001)	(0.001)
No Tenure × Log Firm Size				-0.010***
				(0.000)
3+ Years of Tenure × Log Firm Size				0.007***
				(0.000)
No. of Observations	38,436	115,308	38,436	115,308

Note: This table reports the coefficients obtained from projecting the estimated firm-tenure effects from Eq. 1 on firm-level characteristics. The sample is described in Table D.1b, but is further to restricted to only include firms with mean log value added per worker above 3.75 indicated by the kink in Figure 2. Firm size is averaged over the sample period. The regression using log value-added per worker is weighted by firm-size. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.3. Changes in Log Hourly Wages and Excess Value Added per Worker

	(1)	(2)	(3)
Constant	-0.008***	-0.004***	0.020***
	(0.001)	(0.001)	(0.001)
1-2 Years of Tenure		-0.005***	-0.006***
		(0.001)	(0.001)
No Tenure		-0.009***	-0.006***
		(0.001)	(0.001)
Change in Excess Log Value Added per Worker	0.026***	0.043***	0.029***
	(0.004)	(0.005)	(0.003)
1-2 Years of Tenure × Change in Excess Log Value Added per Worker		-0.012**	-0.006*
		(0.005)	(0.003)
No Tenure × Change in Excess Log Value Added per Worker		-0.040***	-0.019***
		(0.007)	(0.005)
Change in Mean Worker FE (AKM)			0.871***
			(0.005)
No. of Observations	220,324	220,324	220,324

Note: This table reports the coefficients obtained from projecting the change in the firm-year-level mean log hourly wage on the change in excess log value added per worker for each tenure group. Excess log value added per worker is defined as log value-added minus 3.75, corresponding to the kink in Figure 2. This is consistent with Card et al. (2016). Log hourly wages are residualized via an OLS regression including education-specific year dummies and education-specific cubic polynomials in age. The sample is described in Table D.1b. The regression is weighted by firm-size. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.4. DWL variance decomposition of wages.

	DWL Firm Effects	DWL Firm-Tenure Effects
Std. Dev. of Log Hourly Wages	3.284	3.284
Std. Dev. of Log Hourly Wages (Residualized)	0.311	0.311
Number of estimated destination effects	37581.0	109325.0
Number of estimated origin effects	38496.0	103305.0
Std. Dev. destination Fixed Effects	0.108	0.123
Std. Dev. destination Fixed Effects (Bias-Corrected)	0.102	0.115
Fixed Effects Variance Relative to Firm Effects (Destination)	1.0	1.288
Std. Dev. origin Fixed Effects	0.061	0.089
Std. Dev. origin Fixed Effects (Bias-Corrected)	0.053	0.077
Fixed Effects Variance Relative to Firm Effects (Origin)	1.0	2.145

Note: This table reports the variance decomposition after fitting an DWL model as in Eq. 2 with either firm effects or firm-tenure effects to log hourly wages only using the estimation sample defined in Table D.3b. Bias-corrected variance components are estimtated using the leave-out bias correction of Kline et al. (2020) via leaving a worker–firm-tenure match out.

TABLE C.5. Portability of Returns Within Industries and Occupations

	(1)	(2)	(3)
Constant	3.140***	3.133***	3.131***
	(0.002)	(0.002)	(0.002)
Prevous Firm Starting Wage (AKM)	1.002***	1.000***	1.000***
	(0.001)	(0.001)	(0.001)
Prevous Firm Returns to Tenure (AKM)	1.001***	0.994***	0.999***
	(0.001)	(0.002)	(0.003)
Current Firm Firm Tenure FE (AKM)	0.985***	0.981***	0.981***
	(0.001)	(0.001)	(0.001)
Worker FE (AKM)	0.999***	0.998***	0.999***
	(0.001)	(0.001)	(0.001)
Same Industry		0.018***	
		(0.000)	
Same Industry × Prevous Firm Returns to Tenure (AKM)		0.005**	
		(0.002)	
Same Occupation			0.016***
			(0.001)
Same Occupation × Prevous Firm Returns to Tenure (AKM)			0.001
			(0.002)
No. of Observations	2,706,517	2,706,517	2,634,260

Note: This table reports the coefficients obtained from projecting individual log hourly wages on the estimated firm-tenure effects from Eq. 1 for current and previous employers. The slopes are allowed to vary depending on whether current and previous industry (2 digit NACE)or occupation (2 digt ISCO) is the same. The sample is described in Table D.1b. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C.6. Selection into High Starting Wage Firms based on Previous Returns to Tenure

	(1)	(2)	(3)
Constant	-0.019***	-0.070***	-0.101***
	(0.003)	(0.014)	(0.014)
Prevous Firm Starting Wage (AKM)	0.417***	0.414***	0.388***
	(0.019)	(0.020)	(0.018)
Prevous Firm Returns to Tenure (AKM)	0.211***	0.204***	0.197***
	(0.013)	(0.012)	(0.012)
Worker FE (AKM)		0.017***	0.028***
		(0.004)	(0.004)
No. of Observations	2,852,622	2,852,622	2,852,622

Note: This table reports the coefficients obtained from projecting the estimated firm-tenure effects for the "No Tenure" group from Eq. 1 of the worker current employer on the estimated firm-tenure-effects of their previous employer. The sample is described in Table D.1b. Std. Errors are clustered at the firm level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D. Additional Sample Characteristics

TABLE D.1. Summary Statistics - AKM Estimation Samples

	Pooled Sample	No Tenure	1-2 years	3 years or more
Panel (a): AKM Sample				
Number of observations	19,648,192	2,324,291	5,319,611	12,004,290
Number of individuals	2,518,298	1,440,145	1,941,718	2,053,979
Number of person-firm matches	5,006,199	2,324,291	3,326,940	2,552,520
Number of firms	93,557	83,703	91,497	82,164
Number of firm-tenure fixed effects	257,364	83,703	91,497	82,164
Mean log hourly wage	3.257	3.113	3.189	3.315
Std. Dev. of log hourly wage	0.353	0.365	0.367	0.331
Mean tenure (Years)	6.151	0.0	1.431	9.433
Median tenure (Years)	4.0	0.0	1.0	7.0
Panel (b): AKM Sample, Private Sector, Accounting Data and all Tenure Groups				
Number of observations	9,192,372	1,263,522	2,757,683	5,171,167
Number of individuals	1,465,966	858,056	1,126,041	1,016,090
Number of person-firm matches	2,576,528	1,263,522	1,733,421	1,230,033
Number of firms	51,028	51,028	51,028	51,028
Number of firm-tenure fixed effects	153,084	51,028	51,028	51,028
Mean log hourly wage	3.273	3.138	3.206	3.342
Std. Dev. of log hourly wage	0.373	0.359	0.378	0.358
Mean tenure (Years)	5.457	0.0	1.425	8.94
Median tenure (Years)	3.0	0.0	1.0	7.0
Mean log value added per worker	4.151	4.098	4.119	4.18
Std. Dev. of log value added per worker	0.378	0.381	0.386	0.37

Note: Sample D.1a consists of all observations in Sample 1a for which the firm-tenure effect is identified and with a statistical leverage less than 1. Sample 1b consists of observations in Sample 1a belonging to private sector firms, for which value-added data is available and exceeds 26.8k EUR per worker, and for which observations in all firm-tenure effects are identified.

TABLE D.2. Summary Statistics - AKM Separate Estimation Samples

	Pooled Sample	No Tenure	1-2 years	3 years or more
Panel (a): AKM Separate Estimation Sample				
Number of person-job observations	19,480,449	2,317,937	5,314,328	11,848,184
Number of individuals	2,512,912	1,433,879	1,938,852	2,016,487
Number of person-firm matches	4,995,389	2,317,937	3,324,016	2,513,464
Number of firms	93,102	81,394	90,245	69,441
Number of destination fixed effects	241,080	81,394	90,245	69,441
Number of origin fixed effects	209,648	182,018	191,426	131,129
Mean log hourly wage	3.257	3.113	3.189	3.316
Std. Dev. of log hourly wage	0.353	0.364	0.367	0.33
Mean tenure (Years)	6.143	0.0	1.431	9.459
Median tenure (Years)	4.0	0.0	1.0	7.0
Panel (b): AKM Separate Estimation Sample, Private Sector, Accounting Data, and all Tenure Groups				
Number of observations	8,946,555	1,216,554	2,673,596	5,056,405
Number of individuals	1,437,112	834,471	1,098,376	989,554
Number of person-firm matches	2,497,693	1,216,554	1,679,158	1,201,237
Number of firms	42,479	42,479	42,479	42,479
Number of firm-tenure fixed effects	127,437	42,479	42,479	42,479
Mean log hourly wage	3.276	3.141	3.21	3.344
Std. Dev. of log hourly wage	0.373	0.36	0.378	0.358
Mean tenure (Years)	5.499	0.0	1.426	8.975
Median tenure (Years)	3.0	0.0	1.0	7.0
Mean log value added per worker	4.157	4.106	4.126	4.185
Std. Dev. of log value added per worker	0.377	0.381	0.386	0.369

Note: Sample D.2a consists of all observations in Sample 1a for which the firm-tenure effect is identified and with a statistical leverage less than 1 when estimating the effects separately for each tenure group. Sample D.2b consists of observations in Sample D.2a belonging to private sector firms, for which value-added data is available and exceeds 26.8k EUR per worker, and for which observations in all firm-tenure effects are identified.

TABLE D.3. Summary Statistics - DWL Estimation Samples

	Pooled Sample	No Tenure	1-2 years	3 years or more
Panel (a): DWL Sample				
Number of person-job observations	8,361,355	1,677,780	3,588,828	3,094,747
Number of individuals	1,476,550	1,067,041	1,396,793	953,592
Number of person-firm matches	2,929,450	1,677,780	2,251,287	1,068,458
Number of firms	80,138	70,673	77,253	58,663
Number of destination fixed effects	206,589	70,673	77,253	58,663
Number of origin fixed effects	190,899	168,677	174,479	121,969
Mean log hourly wage	3.201	3.096	3.175	3.289
Std. Dev. of log hourly wage	0.374	0.368	0.377	0.352
Mean tenure (Years)	2.372	0.0	1.407	4.777
Median tenure (Years)	2.0	0.0	1.0	4.0
Panel (b): DWL Sample - Private Sector, Accounting Data, Returns Identified				
Number of person-job observations	3,990,838	827,436	1,729,421	1,433,981
Number of individuals	883,192	596,586	772,527	474,929
Number of person-firm matches	1,422,073	827,436	1,081,381	516,868
Number of firms	24,688	24,688	24,651	24,688
Number of destination fixed effects	74,027	24,688	24,651	24,688
Number of origin fixed effects	149,889	126,751	132,156	85,144
Mean log hourly wage	3.218	3.118	3.192	3.306
Std. Dev. of log hourly wage	0.382	0.361	0.385	0.372
Mean tenure (Years)	2.293	0.0	1.406	4.685
Median tenure (Years)	2.0	0.0	1.0	4.0
Mean log value added per worker	4.127	4.106	4.121	4.146
Std. Dev. of log value added per worker	0.392	0.386	0.392	0.393

Note: Sample D.3a consists of all observations in Sample 1a for which the destination and origin firm-tenure effects are identified and with a statistical leverage less than 1. Sample D.3b consists of observations in Sample D.3a belonging to private sector firms, for which value-added data is available and exceeds 26.8k EUR per worker, and for which the "No Tenure" and "3+ Years" destination and origin firm-tenure effects are identified.

TABLE D.4. Summary Statistics - DWL with Transition Types Estimation Samples

	Pooled Sample	No Tenure	1-2 years	3 years or more
Panel (a): DWL with Transition Types				
Number of person-job observations	8,283,954	1,666,233	3,560,899	3,056,822
Number of individuals	1,462,748	1,057,301	1,383,293	943,707
Number of person-firm matches	2,911,749	1,666,233	2,235,529	1,058,160
Number of firms	79,243	69,928	76,323	57,707
Number of destination fixed effects	203,958	69,928	76,323	57,707
Number of origin fixed effects	189,035	166,301	171,776	118,478
Mean log hourly wage	3.201	3.096	3.175	3.29
Std. Dev. of log hourly wage	0.374	0.368	0.378	0.353
Mean tenure (Years)	2.366	0.0	1.407	4.773
Median tenure (Years)	2.0	0.0	1.0	4.0
Panel (b): DWL with Transition Types - Private Sector, Accounting Data, Returns Identified				
Number of person-job observations	2,886,120	588,163	1,246,829	1,051,128
Number of individuals	706,355	459,511	600,559	351,400
Number of person-firm matches	1,017,996	588,163	777,983	375,551
Number of firms	6,967	6,967	6,961	6,967
Number of destination fixed effects	20,895	6,967	6,961	6,967
Number of origin fixed effects	122,111	100,100	105,161	64,053
Mean log hourly wage	3.226	3.125	3.201	3.311
Std. Dev. of log hourly wage	0.383	0.362	0.384	0.374
Mean tenure (Years)	2.32	0.0	1.407	4.701
Median tenure (Years)	2.0	0.0	1.0	4.0
Mean log value added per worker	4.147	4.128	4.142	4.163
Std. Dev. of log value added per worker	0.4	0.392	0.399	0.403

Note: Sample D.4a consists of all observations in Sample 1a for which the destination and origin firm-tenure effects are identified and with a statistical leverage less than 1. Sample D.4b consists of observations in Sample D.4a belonging to private sector firms, for which value-added data is available and exceeds 26.8k EUR per worker, and for which the "No Tenure" and "3+ Years" destination and origin firm-tenure effects for both transition types are identified.

Appendix E. Returns to Tenure in Sequential Auction Models

In Postel–Vinay and Robin (2002) the wage of a new hire who has just been poached from another firm is given by

$$\ln \phi(\epsilon, p, q) = \ln \epsilon + \ln q - \kappa \int_q^p \frac{\bar{F}(x)}{x} dx \tag{E.1}$$

where ϵ is idiosyncratic productivity of the worker, q is the productivity of the previous employee, p is the productivity of the current employee, $1 - \bar{F}(x)$ is the cdf. of the productivity distribution of firms that worker encounter and κ is a function of the offer arrival rate, the discount rate and the exogenous separation rate. As noted by Di Addario et al. (2023) this also be written as

$$\ln \phi(\epsilon, p, q) = \ln \epsilon + I(p) + \ln q - I(q) \tag{E.2}$$

where $I(z) = \kappa \int_z^\infty \frac{\bar{F}(x)}{x} dx$. As time goes on a workers will receive offers from other firms, that might either cause them to leave or receive a raise. In the latter case the wage will given by $\ln \phi(\epsilon, p, p')$ where p' is productivity of the most productive firm that has tried to poach the worker. I will now show that the expected returns to tenure is decreasing in the productivity of a workers previous employer. Let $M_\tau(x)$ denote the cdf. for the maximum draw from $F(x)$ in an interval of length τ. From Mortensen (2003) we know that

$$M_\tau(x) = \sum_{x=0}^{\infty} F(w)^x \frac{e^{-\mu\tau}(\mu\tau)^x}{x!} = e^{-\mu\tau[1-F(x)]} \tag{E.3}$$

where μ is the rate at which a worker encounter poaching firms. The expected wage of a worker after a period of length τ, who was originally poached from a q firm, who has not been poached by a new firm is given by

$$E(\ln \phi_\tau(\varepsilon, p, q)) = \underbrace{\frac{M_\tau(q)}{M_\tau(p)} \ln \phi(\varepsilon, p, q)}_{\text{Outside offer not improved}} + \underbrace{\frac{1}{M_\tau(p)} \int_q^p \ln \phi(\varepsilon, p, x)\, dM_\tau(x)}_{\text{Outside offer improved, Same employer}} \tag{E.4}$$

Note that the division by $M_\tau(p)$ comes from conditioning on that the worker has not been poached again. The expected return to tenure is then given by

$$
\begin{aligned}
& E\left(\Delta \ln \phi_\tau(\varepsilon, p, q)\right) = E\left(\ln \phi_\tau(\varepsilon, p, q)\right) - \ln \phi(\epsilon, p, q) \\
& = \frac{M_\tau(q)}{M_\tau(p)} \ln \phi(\varepsilon, p, q) + \frac{1}{M_\tau(p)} \int_q^p \ln \phi(\varepsilon, p, x)\, dM_\tau(x) - \ln \phi(\varepsilon, p, q) \\
& = \frac{1}{M_\tau(p)} \int_q^p \ln \phi(\varepsilon, p, x)\, dM_\tau(x) - \frac{M_\tau(q) - M_\tau(p)}{M_\tau(p)} \ln \phi(\varepsilon, p, q) \\
& = \frac{1}{M_\tau(p)} \int_q^p \left(\ln \phi(\varepsilon, p, x) - \ln \phi(\varepsilon, p, q)\right) dM_\tau(x)
\end{aligned}
\tag{E.5}
$$

Inserting Eq. E.7 then results in

$$
E\left(\Delta \ln \phi_t(\varepsilon, p, q)\right) = \frac{1}{M_t(p)} \int_q^p \left((\ln x - I(x)) - (\ln q - I(q))\right) dM_t(x) \tag{E.6}
$$

which is the same as Eq. 5 in Section 5.

Bagger et al. (2014) builds on Postel–Vinay and Robin (2002) by allowing for general returns to experience and bargaining. Di Addario et al. (2023) show that the hiring wage can be written as

$$
\ln \phi(\epsilon, p, q, \chi, \varepsilon|\beta) = \ln \alpha(\epsilon) + g(\chi) + \varepsilon + \beta \ln p + I(p|\beta) + (1-\beta) \ln q - I(q|\beta) \tag{E.7}
$$

where χ is labor market experience, ε is a transitory worker-specific shock, and β is the share of the surplus received by the worker from bargaining.[14] Using the same steps as before, the expected returns to tenure can be written as

$$
\begin{aligned}
& E\left(\Delta \ln \phi_t(\varepsilon, p, q)\right) \\
& = \frac{1}{M_t(p)} \int_q^p \left(((1-\beta) \ln x - I(x|\beta)) - ((1-\beta) \ln q - I(q|\beta))\right) dM_t(x) + \Delta g(\chi)
\end{aligned}
\tag{E.8}
$$

where $\Delta g(\chi)$ denotes the change in wages due to general returns to experience. From Eq. E.8 it is clear that the qualitative predictions are unchanged by the introduction of bargaining and returns to experience: The expected returns to tenure is increasing in the current firms productivity and decreasing in the previous firms productivity.

[14] $I(z|\beta) = (1-\beta)^2 \kappa \int_z^\infty \frac{BarF(x)}{x} \frac{1}{1+\kappa\beta \bar{F}(x)} dx$ which is decreasing in both z and β.