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Firm-specific Human Capital Accumulation: Evidence from Brazil*

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Abstract

We introduce firm-specific returns to experience and tenure into a standard two-way fixed effects model, show that they are separately identified under the standard exogenous mobility assumption and with sufficient between firm mobility, and provide a new evidence on heterogeneity of returns to experience and tenure across firms using the administrative data from Brazil over the years 1999–2014. We document that (1) returns to tenure are not strongly related to firm wage premia, (2) returns to experience are strongly negatively correlated with firm wage premia, (3) the relationship between firm wage premium and return to experience is stronger for 'blue collar' firms.

I. Introduction

Some prominent models of the labour market (Burdett and Coles, 2003, Stevens, 2004, Shi, 2009) predict that in equilibrium firms may offer both different starting wages and different returns to tenure and/or experience. Intuitively, firms that offer low entry wages may compensate workers by offering higher returns to tenure in order to reduce worker turnover. Similarly, firms may reward past experience differently or, alternatively, offer high wage premia irrespective of experience in order to attract most productive workers. Which of these strategies prevails is an empirical question.[1]

Labour economists have long acknowledged heterogeneity in wage premia paid by different firms by including firm fixed effects into panel data wage regressions (see e.g. Abowd, Kramarz, and Margolis, 1999 [AKM, henceforth], Card, Heining, and Kline, 2013). However, studies documenting heterogeneity in *both* return to experience

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[1]In the context of Burdett and Coles (2003) model, where the equilibrium is characterized by a baseline salary scale with different firms starting at different points of that scale, the question of correlation between starting wage premia and tenure returns is a question about concavity of the baseline salary scale.

and tenure are scarce. We extend the standard two-way fixed effects model by allowing the experience and tenure premia to vary across firms and show that one can identify all worker- and firm-specific coefficients provided there is enough mobility between firms, under the standard exogenous mobility condition. We estimate the model by OLS using the Brazilian matched employer-employee data on large firms (>100 workers) over the period 1999–2014. The data contains over 11 million workers and over 11,000 firms, which allows us to estimate heterogeneity across multiple dimensions.

We use the model to document the heterogeneity in returns to experience and tenure and correlation between these returns and other firm-level variables. Our main findings are:

- Returns to experience are strongly inversely related to firm-specific wage premia (i.e. firm fixed effects) whereas this relationship is much weaker for returns to tenure.
- The relationship between firm wage premium and return to experience is stronger for 'blue collar' firms (i.e. firms with low average level of education).

These findings, among others, confirm that, on average, firms with low wage premia (conditional on all other characteristics and worker fixed effects) compensate workers by rewarding their labour market experience well.

Secondly, we provide a new decomposition of log wage variance distinguishing the contribution of firm-specific experience/tenure premia. Although there is substantial variation in tenure returns across firms, its contribution to the wage variance is negligible. Also, as the returns to experience are negatively correlated with firm-specific wage premia, heterogeneity acts towards decreasing wage inequality here. Thus, the overall contribution of heterogeneity in experience/tenure returns to wage inequality is small.

Our analysis also provides new estimates of the return to tenure under the assumption that workers sort themselves across firms based on firm-specific wage premia and firm-specific experience and tenure premia. We estimate the return to 5 years of tenure at 11.4%[2]. Additionally, the return to tenure increases compared to the standard model that does not include firm-specific experience and tenure premia, which suggests that, by estimating firm-specific returns to experience and tenure, our model could remove some of the downward bias in the standard model in line with the reasoning in Topel (1991). Importantly, we argue that our results are not driven by limited mobility bias or are an artefact of a correlated estimation error. In fact, we show that bias correction proposed recently by Kline, Saggio, and Sølvsten (2020) has little effect on variances and correlations of firm and worker fixed effects in our context.

Although we find small correlations between tenure returns and initial wage premia, the signs of the correlations are in line with the agency theory of wage setting (Lazear, 1981, see also discussion in Zwick, 2011). In particular, tenure returns are negatively correlated with initial wage premia and the negative relationship is stronger among larger firms and white-collar firms, so groups of firms that are expected to suffer from a stronger agency problem.

[2]The 5-year average tenure return of 11.4% is estimated from the nonlinear model (see Table 13).

Related literature

Polachek and Kim (1994) contain an early effort in introducing individual-specific slope coefficients into panel data regressions. AKM allow firm-specific returns to tenure, but keep returns to experience constant across firms. They do not analyze the distribution of returns to tenure across firms in detail. Additionally, their model produces very different mean returns to tenure across different estimation methods (see table IV in their article). Abowd, Kramarz, and Roux (2006) introduce firm-specific returns to tenure into a model of wages and mobility with multivariate normal employment and mobility shocks with zero restrictions on their covariance matrix. Zwick (2011) analyzes correlations between firm-specific tenure premia and observed characteristics. More recently, Gregory (2020) documents heterogeneity in the wage-tenure profiles across firms in Germany using an auxiliary two-way fixed effect model for wage dynamics (see also Guvenen, 2009 for an earlier contribution). Similarly to our article, Dustmann and Meghir (2005) allow for varying returns to tenure and experience across firms and workers but do that within a correlated random coefficients model, whereas we allow the coefficients to be correlated with covariates included in the model. They identify and discuss only the mean returns and do not investigate how experience/tenure returns are correlated with firm fixed effects. Arellano-Bover and Saltiel (2021) analyze heterogeneous returns to experience, without heterogeneity in returns to tenure, but allow only 10 different values (classes) of returns across firms which severely restricts heterogeneity compared to our study.

We estimate reduced form panel wage regressions. There is a large structural literature that incorporates various forms of heterogeneity in wage returns (see e.g. Belzil and Hansen, 2002, Belzil and Hansen, 2007, Belzil, Hansen, and Liu, 2017, and especially Belzil and Hansen, 2001). However, authors in this literature are able to introduce very limited number of ‘types’, usually in single digits, and employ a random coefficients assumption, whereas we estimate separate coefficients for each firm (i.e. more than 10,000 coefficients) and allow them to be correlated both with observed characteristics and unobserved ability (worker and firm fixed effects). Of course, we can achieve this flexibility due to the fact that we do not extensively model mobility as these papers do.

Other papers performing wage inequality decompositions using two-way fixed effects models for *Relação Anual de Informações Sociais* (RAIS) data include Lopes de Melo (2018), Engbom and Moser (2022), Alvarez *et al.* (2018). Finally, for a recent contribution to the discussion about estimation of homogeneous tenure and experience returns see Snell *et al.* (2018).

II. Econometric model

We use the following model for real wages:

$$\log W_{ijt} = \alpha_i + \phi_j + \lambda_t + \gamma_j^S Ten_{ijt} + \gamma_j^G Exp_{it} + u_{ijt}, \tag{1}$$

where W_{ijt} is real hourly wage of worker i in firm j at time t, α_i is worker fixed effect (FE), ϕ_j is firm fixed effect, λ_t is year fixed effect, Ten_{ijt} is tenure of worker i in firm j at time t, and Exp_{it} is actual experience of worker i at time t.

Thus, compared to the standard model (referred in this article as the homogeneous model) we allow the experience and tenure coefficients to vary between firms. We adopt the convention that W_{ijt} is the beginning of period wage, that is, that it accounts for returns to tenure and experience in the previous period but not in the current one. Also note that, just as AKM, we require access to data on actual experience (i.e. career breaks) in order to separately identify time effects, worker FEs and returns to experience.

Let $J(i,t)$ denote the function that identifies worker i's employer at time t. Once we control for firm-specific returns to experience and tenure we impose the following exogenous mobility assumption.

Assumption 1. We have:

$$
\begin{aligned}
&E[u_{ijt}|i,t,\text{Ten}_{ijt},\text{Exp}_{it},J(i,t)=j]\\
&\quad = E[u_{ijt}|i,t,\text{Ten}_{ijt},\text{Exp}_{it},J(i,t)=J(i,t-1)=j]\\
&\quad = E[u_{ijt}|i,t,\text{Ten}_{ijt},\text{Exp}_{it},J(i,t)=j\neq J(i,t-1)]=0.
\end{aligned}
$$

This assumption implies that in our model the error term u_{ijt} represents market-wide shocks, measurement error etc. and workers do not sort themselves across firms based on u_{ijt}. In particular, the error term has mean zero both for workers staying at the firm ('stayers') and moving to another company ('movers'). Note that this assumption is weaker compared to a corresponding assumption in the homogeneous model as our model already separates differential wage contract terms with respect to experience and tenure premia from u_{ijt}.

Identification

We estimate our model by OLS. Thus, identification follows from a standard rank condition on the matrix of observables and fixed effect dummies. In order to gain some more insight into the sources of identification of firm-specific tenure and experience effects (γ_j^S and γ_j^G) we look at the wage dynamics among stayers and movers. Identification of the model parameters consists of the following steps:

1. Identify $\gamma_j^S+\gamma_j^G$ up to an additive scalar γ_0 from the wage dynamics among *stayers*:

$$\log\frac{W_{ijt}}{W_{ijt-1}}=\lambda_t-\lambda_{t-1}+\gamma_j^S+\gamma_j^G+u_{ijt}-u_{ijt-1},$$

as $E[u_{ijt}-u_{ijt-1}|i,t,J(i,t)=J(i,t-1)=j]=0$ under Assumption 1.

2. Identify γ_j^S from the wage dynamics among *movers*:

   - Note that for *movers* from firm j to j' we have:[3]

$$
\begin{aligned}
\log\frac{W_{ij't}}{W_{ijt-1}}=\lambda_t-\lambda_{t-1}+\phi_{j'}-\phi_j+\gamma_j^G-\gamma_j^S Ten_{ijt-1}\\
+\left(\gamma_{j'}^G-\gamma_j^G\right)Exp_{it}+u_{ij't}-u_{ijt-1}.
\end{aligned}
\qquad (2)
$$

[3]Note that since $W_{ij't}$ is the beginning-of-period wage, the returns to tenure in firm j' do not feature in the equation.

- Now subtracting the mean across all movers from j to j':

$$\log\frac{W_{ij't}}{W_{ijt-1}} - \frac{1}{\mathrm{TN}_{\mathrm{movers}}}\sum_{t=1}^{T}\sum_{\mathrm{movers}\quad j\to j'}\log\frac{W_{ij't}}{W_{ijt-1}}$$
$$= -\gamma_j^S(\mathrm{Ten}_{ijt-1} - \mathrm{Ten}_{\cdot j\cdot}) + \left(\gamma_{j'}^G - \gamma_j^G\right)(\mathrm{Exp}_{it} - \mathrm{Exp}_{\cdot\cdot})$$
$$+ u_{ij't} - u_{ijt-1} - (u_{\cdot j'\cdot} - u_{\cdot j\cdot}), \tag{3}$$

  which identifies γ_j^S's under Assumption 1 and having at least two movers from j to some j' with different tenure levels. Here $X_{\cdot j\cdot}$ or $X_{\cdot\cdot}$ means an average of X over all movers from j to j' over time.

3. Now as we have identified γ_j^S and $\gamma_j^G - \gamma_0$, define $\log\widetilde{W}_{ijt} = \log W_{ijt} - \gamma_j^S\mathrm{Ten}_{ijt} - (\gamma_j^G - \gamma_0)\mathrm{Exp}_{it}$. Finally, α_i, ϕ_j, λ_t, and γ_0 (and, thus, γ_j^G) can be identified using standard arguments, that is, we need firms to be 'connected' by mobility of workers between them and we need Exp_{it} to measure actual experience, from:

$$\log\widetilde{W}_{ijt} = \alpha_i + \phi_j + \lambda_t + \gamma_0\mathrm{Exp}_{it} + u_{ijt}.$$

Step 2 requires some discussion. Note that equation (3) is trivially satisfied and does not provide any identifying power if there is only one mover from firm j to firm j' over the sample period. On the other hand, the tenure coefficient on the right-hand side of (3) does not depend on j', which implies that in order to identify γ_j^S in practice we need at least two workers moving from company j to *some* company j' (with different values of tenure in firm j). In principle, this restricts us to focus on larger companies.[4] This condition can be verified by looking at the adjacency matrix in the firm network, i.e. network between firms where links are created by worker mobility – for each firm we require at least one directed link with multiplicity two.[5]

When it comes to the last step, Jochmans and Weidner (2019) show that precise estimation of worker and firm fixed effects requires good level of mobility between firms, which is captured by measures of global connectivity of the bipartite employer–employee network and the firm network (where connections between firms are formed by job switchers). Appendix A contains analysis of these networks in our RAIS data.

We note that our specification in (1) does not include nonlinear terms for experience and tenure. Identification of firm-specific coefficients corresponding to nonlinear terms in experience and tenure would follow similar arguments. With nonlinear terms, step 2 would identify both linear and nonlinear firm-specific coefficients. In practice, it will be difficult to identify piecewise linear functions of tenure (or experience), often used in the literature, as this will require at least two movers from j to j' for each interval in the linear

[4] An alternative, alas much more computationally involved, approach would use the grouping estimator of Bonhomme, Lamadon, and Manresa (2022).

[5] Building a directed firm network may sometimes be challenging as one has to take into account timing of the worker moves, for example, a link formed by a worker being at time $t-1$ in j and in j' at t has an opposite direction than a link from a worker in j' at time $t-1$ and in j at t. One can then use data from the undirected network, which usually is easier to analyze, to get some proxy for the magnitude of the moves.

spline. Thus, we focus on polynomial specifications of tenure and experience profiles (see section VI), with a view that variation in tenure across movers from j to j' will contain some information on the curvature of these parametrically restricted profiles.

III. Data: RAIS

The data used in this paper come from the RAIS, a matched employer–employee dataset assembled by the Brazilian Ministry of Labour and Social Security. The data is based on yearly reports submitted by firms who are required by law to do so and face fines if they do not. The data contains unique social security identifiers of workers (*PIS*) and firms (*CNPJ*), which allows us to track them over the sample period, 1999–2014.[6]

Our sample includes private sector firms with over 100 workers.[7] We focus on the group of working age males. As job switchers are really important for identifying and estimating the firm-specific coefficients in our model we drop firms with less than 10 job movers over the sample period, which leaves 89% of firms and 98% of workers from the initial sample. Additionally, we drop all workers with inconsistent entries on education or age within the sample, namely, workers for which we record a drop in years of education or age, which excludes 13.9% of workers in the sample. After scrutinising these cases we conclude that the inconsistencies mainly result from mistakes in entering the data by the companies, in particular recording data under the wrong worker identifier (*PIS*).[8] Finally, we select the largest connected component of the firms network (where edges are formed by worker mobility). As we already focus on large firms with significant mobility the largest component contains 99.5% of firms and more than 99.99% of workers.

As we do not observe the full history of employment for each worker we approximate experience by $Exp_{it} = Exp_i^0 + Exp_{it}^{99-14}$ where Exp_i^0 is the potential experience (i.e. age - years of education - 6) at the entry to the panel and $\mathrm{Exp}_{it}^{99-14}$ is the time spent in the panel up to time t. One way to interpret Exp is that it measures formal sector experience. We generate hourly wage by dividing the monthly salary by the number of contracted hours and then deflate the wages using the CPI index. Table 1 contains the summary statistics. Our final sample includes 11,218 firms and more than 11 million workers. The average wage is equal to 22 Brazilian Real (in 2010 Reals), which amounts to approximately \$5 per hour.

Figure 1 displays the trends in the data. Brazil experienced dynamic economic growth during 1999–2014, with the real wage tripling in this period. This period also saw a steady rise in the average education level. The average tenure and experience are fairly stable across time, with a slight uptick towards the end of the sample. The latter is caused by the fact that we exclude workers who spent only one year in the panel, which, as a result, excludes young workers entering the job market in 2014 as well as young workers switching in and out of employment in the final years of the sample.

[6] See Dix-Carneiro (2014) for a more detailed description of RAIS.
[7] In Appendix C we relax this restriction to 50+ workers and obtain similar results.
[8] The dropped workers spend, on average, two more years in the panel, are more experienced and come predominantly from large companies. As probability of at least one mistake in the records increases with worker's time in the sample and large companies are more likely to confuse worker identifiers, this suggests that these mistakes are due to data entry errors.

TABLE 1
Summary statistics

	Mean	*SD*	*Min.*	*Max.*
Wage (in 2010 Reals)	22.0	34.8	0.4	1739.8
Tenure (in years)	5.1	6.1	0.0	45.0
Experience (in years)	19.0	10.4	0.0	45.0
Years of education	9.4	3.2	0.0	21.0
NT	62,627,774			
J	11,218			
N	11,054,444			

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014. (ii) *J*, *N* and NT denote the number of firms, the number of employees and number of observations in RAIS, respectively.

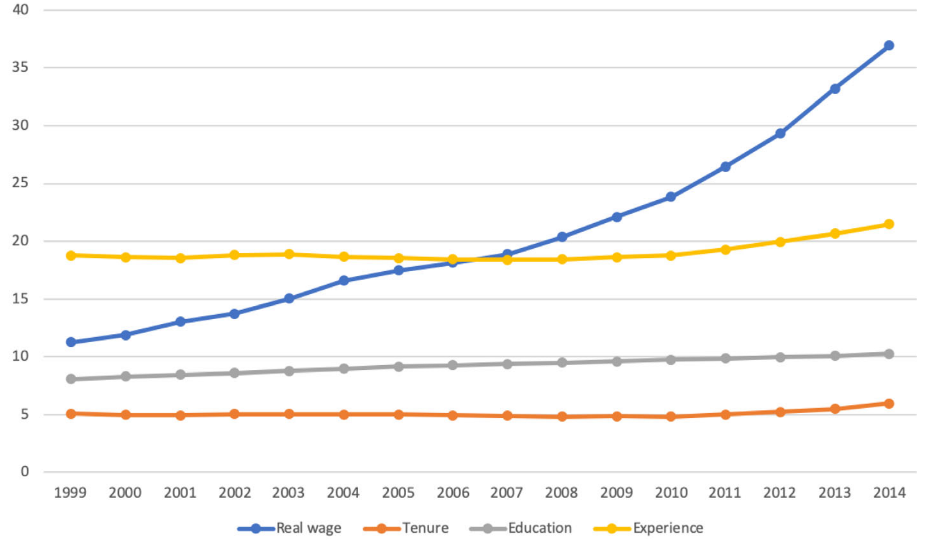

Figure 1. Trends in the RAIS data.
Notes: (i) All data points correspond to averages for a given year; (ii) Education is measured by years of completed education [Colour figure can be viewed at *wileyonlinelibrary.com*]

IV. Results

We estimate our model by ordinary least squares using the iterative LSMR method of Fong and Saunders (2011). As the model includes many firm-specific coefficients we discuss the fit of the model and the estimates of the common coefficients first and then analyze the variation in the firm-specific coefficients.

Importantly, although the reported sample variances and covariances of the firm-specific coefficients and fixed effects may suffer from a limited mobility bias, in section VI we show that this bias is unlikely to bear any consequences for these estimates and the resulting conclusions.

As mentioned above, our model in (1) does not include a nonlinear profile in experience and tenure. This simplifies the exposition of results and implies that the experience and tenure coefficients should be interpreted as linear approximations to the possibly nonlinear profiles. We show in section VI that including diminishing returns to experience and tenure leads to the same conclusions.

Coefficient estimates and fit

We compare estimates of our model in (1) to a standard two-way fixed effects model and a model with heterogeneous effect of experience but homogeneous effect of tenure in Table 2.

As in other two-way fixed effect studies the models fit the data quite well, explaining around 92.5% variation in real wages in Brazil. Although including firm-specific returns to experience and/or tenure introduces many new coefficients into the model, it moderately improves the fit to the wage data (see the increase in adjusted R^2).

Heterogeneous coefficients

Table 3 contains summary statistics of the estimated worker and firm fixed effects and firm-specific experience and tenure coefficients. The mean return to an additional year of experience is 1.3%, only slightly higher than the estimate from the homogeneous model in column (1) of Table 2, whereas the mean return to tenure is 1.6% per year compared to 1% from the homogeneous model. As argued by Topel (1991) simply regressing wages on experience, tenure and fixed effects does not produce unbiased estimates of returns to tenure as workers will sort themselves across firms based on remuneration packages offered by different firms. Intuitively, by allowing heterogeneous returns to experience and tenure we control for differential rewards provided in wage contracts offered by different firms and, in line with Topel's intuition, this seems to remove a part of the downward bias in the estimated mean return to tenure.

We find much larger variation in the returns to tenure (coefficient of variation, CV, equals 1.75) than in the returns to experience (CV $= 0.7$) across firms. Thus, we conclude that firms differ significantly in how they remunerate tenure. The last column of Table 3

TABLE 2

Results: common coefficients and measures of fit

	(1)	*(2)*	*(3)*
Exp	0.011871***		
	(249.469)		
Ten	0.010226***	0.010417***	
	(574.840)	(566.815)	
Worker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Het. Exp coeff.	No	Yes	Yes
Het. Ten coeff.	No	No	Yes
NT	62,721,402	62,722,307	62,721,402
R^2	0.924	0.926	0.927
Adjusted R^2	0.907	0.910	0.911

Notes: (i) t-statistics are given in parentheses; (ii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (iii) NT denotes the number of observations in the RAIS.
*** indicates statistical significance at the 1 % level.

TABLE 3
Heterogeneous coefficients

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Worker FE	0.000	0.601	0.369	
Firm FE	0.101	0.320		0.369
Exp	0.013	0.009	−0.507	−0.038
Ten	0.016	0.028	−0.085	−0.037

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

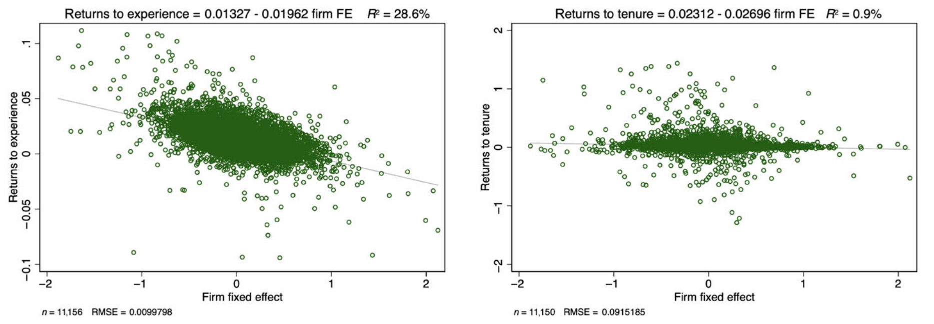

Figure 2. Heterogeneous coefficients: return to experience (left) and tenure (right) vs. firm fixed effect.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

shows clear evidence of assortative matching between firms and workers, in terms of more able/productive workers matching with firms with higher starting wage premia ($\text{Corr}(\alpha_i, \phi_j) = 0.369$).

Finally, the results in the third column of Table 3 suggest that the wage contracts in Brazil compensate high starting wage premia (i.e. high ϕ_j) with lower returns to experience (γ_j^G). However, the relationship between the wage premia and the returns to tenure (γ_j^S) is negligible. This is also illustrated in Figure 2 which shows that the firm-specific wage premia explain 28.6% of variation in the firm-specific returns to experience whereas they hardly explain any variation in the firm-specific tenure premia.[9]

Interestingly, Figure 3 shows that the returns to experience and tenure are not correlated. Thus, firms which reward initial experience well do not seem to reward well firm tenure at the same time. Other interpretation is that firms which reward general labour market experience well do not really build a lot of firm-specific human capital.

Additionally, if we measure the mean quality of workers in a firm by the average worker fixed effect (over workers and time), we can investigate how the experience and tenure premia are related to characteristics of the workers. Figure 4 illustrates our findings.

[9]We exclude outliers from the figures by dropping bottom and top 0.1% of the observations. The outliers usually correspond to imprecisely estimated effects for firms which spend only a few years in the sample.

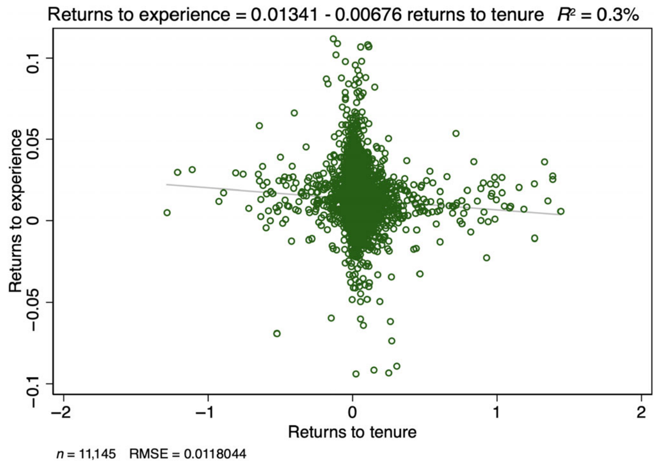

Figure 3. Heterogeneous coefficients: return to experience vs. return to tenure.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

Figure 4. Heterogeneous coefficients: return to experience (left) and tenure (right) vs. mean worker fixed effects.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

The returns to tenure do not seem to be related to the average worker quality at the firm level at all.

Overall, our findings support a view of wage contract setting in which firms differ significantly on how they remunerate loyalty but, in general, they compensate low wage premium (conditional on observed characteristics) with better reward for labour market experience.

Analysis for subpopulations

In this section we try to shed some light at the regularities detected above by looking at different subpopulations of firms. We focus mostly on the relationship between the returns to experience and the firm fixed effects as we do not find any clear patterns when looking at the returns to tenure (Table D2).

Differences between industries

One may argue that wage setting mechanisms will vary largely between industries, for example in some sectors the accumulated experience may be of little importance so firms will compete for workers mainly by offering attractive starting wage premia. Thus, the negative correlation shown in Figure 2 may be fully explained by inter-industry differences. We address this conjecture by looking at the correlation between the experience premia and the firm fixed effects for the services sector and the production and construction sector. Table 4 and Figure 5 illustrate the results (Figures D1 and D2).

Table 4 shows that companies in production and construction pay larger experience and tenure premia than those in services. There seem to be important differences also in pay policies between these two sectors—with firms attracting more productive workers

TABLE 4

Heterogeneous coefficients for two industries

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Panel A. Services				
Worker FE	0.000	0.596	0.347	
Firm FE	0.136	0.305		0.347
Exp	0.009	0.010	−0.495	0.090
Ten	0.010	0.030	−0.134	0.017
Panel B. Production and construction				
Worker FE	0.000	0.619	0.403	
Firm FE	0.139	0.327		0.403
Exp	0.014	0.008	−0.526	−0.122
Ten	0.017	0.024	−0.028	−0.076

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

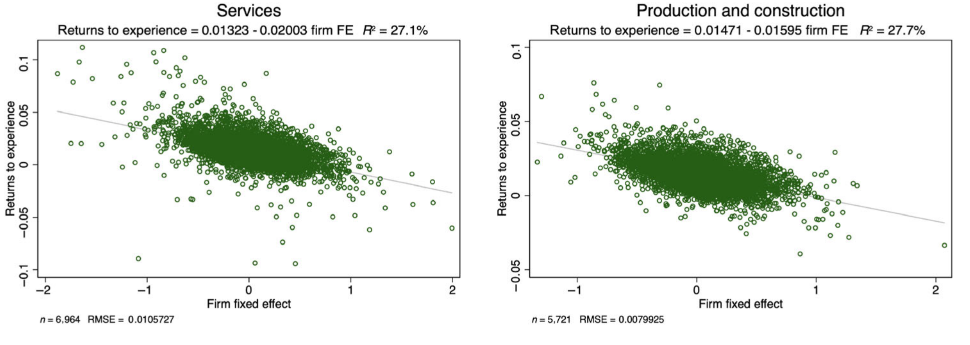

Figure 5. Returns to experience versus firm fixed effects: industry differences.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

(i.e. higher worker FE) paying larger human capital premia in services, and to the contrary in production and construction. The inverse relationship between the firm fixed effects and the experience returns is present in both sectors and is slightly stronger in the production and construction sector ($\text{Corr}(\phi_j, \gamma_j^G) = -0.526$ in comparison to $\text{Corr}(\phi_j, \gamma_j^G) = -0.495$).

Overall, the inter-industry differences do not seem to explain our findings. If anything, slightly weaker correlation found in the service sector suggests that the relationship may be weaker among firms requiring high skilled labour. We investigate this conjecture in the next section.

Blue collar vs. white collar firms

We distinguish 'blue collar' and 'white collar' firms by the average level of education of their workers. Blue collar firms are companies in the first quartile of the average education distribution and white collar firms correspond to the fourth quartile.

As shown in Table 5, although there is no big difference in the mean returns to experience or tenure between the two groups of firms, as expected the average of firm fixed effects is apparently lower for the blue collar firms (−0.077) in comparison to the white collar firms (0.296). Additionally, the relationship between the returns to experience and the firm wage premia is stronger for the blue collar firms, with the coefficient of determination at 41.7% (see Figure 6). Thus, our results suggest that the apparent substitutability between firm wage premia and experience returns is stronger among low skilled workers ($\text{Corr}(\phi_j, \gamma_j^G) = -0.658$). This reflects that jobs with low skill requirements usually have a lower initial wage due to the low entry barriers (which manifests itself with low average firm FE), but the wage grows fast with the accumulation of experience and proficiency of skills.

Our results show that relationship between initial wages and returns to tenure is stronger in the white-collar firms, $\text{Corr}(\gamma_j^S, \phi_j) = -0.197$, in comparison to $\text{Corr}(\gamma_j^S, \phi_j) = -0.084$ in the blue-collar firms, which is in line with the agency theory of the labour market (Lazear, 1981). This theory predicts that it is more advantageous for companies

TABLE 5

Heterogeneous coefficients for blue collar and white collar firms

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Panel A. Blue collar				
Worker FE	0.000	0.490	0.248	
Firm FE	−0.077	0.264		0.248
Exp	0.015	0.007	−0.658	−0.150
Ten	0.012	0.033	−0.084	−0.040
Panel B. White collar				
Worker FE	0.000	0.680	0.302	
Firm FE	0.296	0.349		0.302
Exp	0.013	0.011	−0.493	−0.013
Ten	0.018	0.028	−0.197	−0.132

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

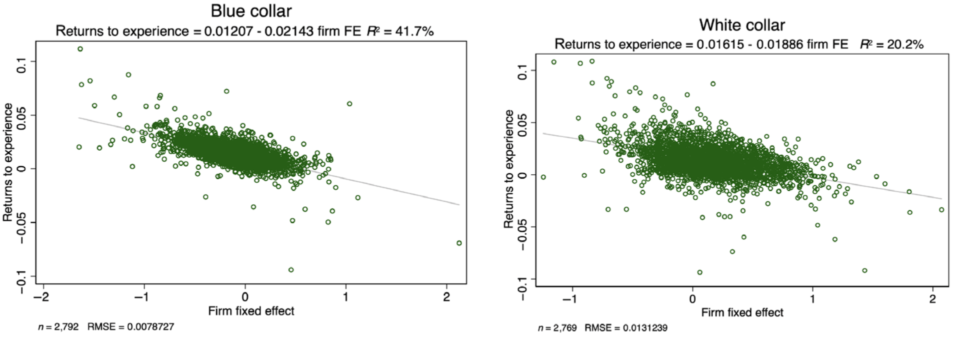

Figure 6. Returns to experience vs. firm fixed effects: blue collar (left) and white collar (right) firms.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

with a predominantly white-collar workforce to offer implicit wage contracts with backloaded wage payments because white-collar workers have lower mobility costs and/or better outside options and it costs more to motivate and retain them than blue-collar workers.

Differences between small, medium, and large firms
With respect to firm size, we divide firms into three groups based on the average level of the number of workers in each firm over the sample period. The small firms are companies with less than 292 workers (first tercile)[10], and the number of workers in the medium firms ranges from 292 to 657 (second tercile). For the large firms, the number of staff is greater than 657 (third tercile).

Large firms are more capable of providing higher wage premium in wage setting in comparison to smaller firms, thus, as expected, Table 6 shows that large firms offer a much higher average wage premium (0.121) compared to small firms (0.014). However, we see that the returns to experience for different firm sizes are very close to each other.[11]

As shown in Figure 7, the negative correlation between the returns to experience and the firm fixed effects weakens with growing firm size. The variation in firm FE explains 34.1% of the variation in returns to experience among the small firms compared to 25.8% among the largest firms. Thus, among the small firms wages of workers starting their jobs in low-pay-premium companies are more likely to catch up with wages of their counterparts starting in high-pay-premium companies, than among the larger firms. Though, the differences here are not as stark as between the blue- and white-collar firms in section IV.

Interestingly, the absolute value of correlation between the tenure premia and the firm fixed effects increases with firm size, which is, again, in line with the agency theory as larger firms are expected to face more severe agency problems, thus have to backload wage payments more.

[10]Recall that we restrict our sample to firms employing more than 100 workers.
[11]This may be caused by the fact that we already focus on relatively large companies.

TABLE 6

Heterogeneous coefficients: firm size

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Panel A. Small firms				
Worker FE	0.000	0.576	0.311	
Firm FE	0.014	0.292		0.311
Exp	0.012	0.010	−0.583	−0.069
Ten	0.016	0.047	−0.064	−0.018
Panel B. Medium firms				
Worker FE	0.000	0.566	0.302	
Firm FE	0.051	0.285		0.302
Exp	0.012	0.009	−0.524	−0.012
Ten	0.016	0.035	−0.083	−0.026
Panel C. Large firms				
Worker FE	0.000	0.611	0.387	
Firm FE	0.121	0.327		0.387
Exp	0.013	0.009	−0.508	−0.041
Ten	0.015	0.023	−0.095	−0.047

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

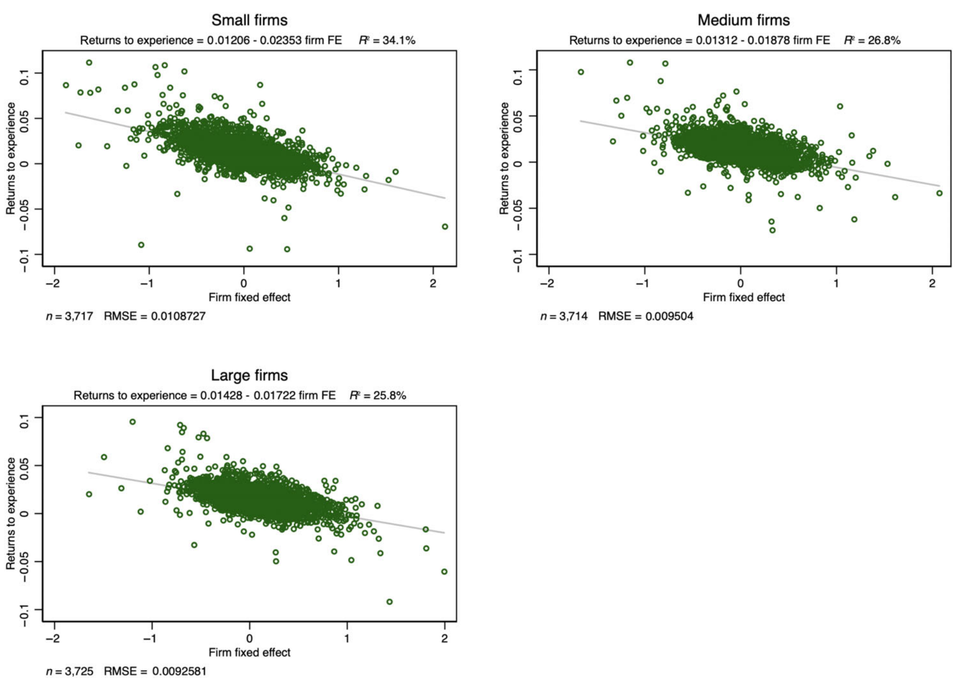

Figure 7. Returns to experience vs. firm fixed effects: firm size.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

Heterogeneous effects and firm age

Companies with a longer history may be more capable of proving higher wage premium in wage setting in comparison to young firms (see Brown and Medoff, 2003 and references therein for a detailed discussion). On the other hand, firms with worse prospects of survival in the market may have to offer higher returns to experience and tenure than more established companies in order to attract workers and control turnover.

We investigate these conjectures by looking at differences in our estimates between young and old companies. As the actual age of firms is unavailable in our data, we use the time spent in the sample as a proxy for firm's age. The median time spent in the sample is 16 years, which is also the maximum value. Thus, we define the old firms as those which are present throughout our sample period 1999–2014 and the young firms as the rest.

Our results in Table 7 confirm the first conjecture, showing that, controlling for worker characteristics and fixed effects, younger firms offer on average lower pay premia (0.076) than old firms (0.110), though the difference is not very large. This result is in line with findings of Davis and Haltiwanger (1991) for the USA.

Further, Table 7 and Figure 8 show that the negative relationship between the wage premium and the return to experience is stronger for the old companies ($\mathrm{Corr}(\phi_j, \gamma_j^G) = -0.443$ and the firm FEs explain 31.3% of variation in the experience returns in this group) but the difference in magnitude is not so apparent. Interestingly, the negative correlation between the tenure returns and the firm fixed effects is stronger among the old firms (−0.115) than the young firms (−0.072). If taken at face value, these results would support the 'implicit contract' hypothesis behind the relationship between firm age and wages (cf. Baker, Gibbons, and Murphy, 1994)—longer functioning firms can more credibly promise higher wages in the future for working hard now. Thus, they can offer steeper wage profiles compensating initially low wage with large rewards for loyalty to the firm.

TABLE 7

Heterogeneous coefficients: firm age

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Panel A. Old firms				
Worker FE	0.000	0.603	0.384	
Firm FE	0.110	0.324		0.384
Exp	0.013	0.009	−0.534	−0.084
Ten	0.014	0.017	−0.115	−0.037
Panel B. Young firms				
Worker FE	0.000	0.593	0.322	
Firm FE	0.076	0.305		0.322
Exp	0.014	0.010	−0.443	0.073
Ten	0.019	0.046	−0.072	−0.041

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

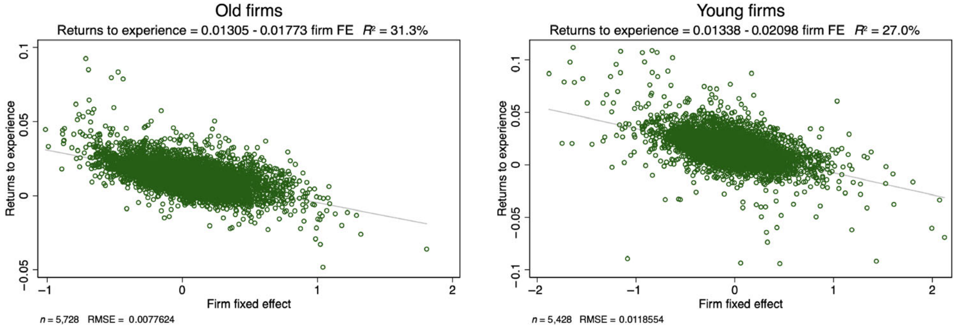

Figure 8. Returns to experience vs. firm fixed effects: firm age.
Notes: (i) Each point represents a combination of estimated return to experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

V. Variance decompositions

We have shown that there is significant variation in returns to experience and, particularly, tenure across firms. In this section we quantify the contribution of this variation to wage inequality.

Importance of heterogeneous effects

In the standard model the role of general and firm-specific human capital is associated with the contribution of the experience, $\gamma^G \text{Exp}_{it}$, and tenure, $\gamma^S \text{Ten}_{ijt}$, components to wage variance. As our model allows the returns to experience and tenure to vary across firms, we can further decompose the variation in the experience, $\gamma_j^G \text{Exp}_{it}$, and tenure, $\gamma_j^S \text{Ten}_{ijt}$, components into the between and within firm variation:

$$\text{Var}(\gamma_j^S \text{Ten}_{ijt}) = \underbrace{\text{Var}(E(\gamma_j^S \text{Ten}_{ijt} | J(i,t) = j))}_{\text{between firms}} + \underbrace{E(\text{Var}(\gamma_j^S \text{Ten}_{ijt} | J(i,t) = j))}_{\text{within firms}},$$

and similarly for experience.

Within variation can be associated with variation of worker experience and tenure whereas between variation is related to cross-firm differences in returns to human capital. Table 8 shows that, in our Brazilian sample, the variation in workers experience and tenure are equally important determinants of the variation in the general human capital as the differences in returns to experience and tenure. Thus we conclude that the differences in returns between firms are an important determinant of inequality in both general and specific human capital accumulation. However, as we are going to see later, variation in these returns plays only a minor role in shaping overall wage inequality.

Wage variance decomposition

Introducing firm-specific returns to experience and tenure changes the specification of the standard model and, thus, leads to different estimates of firm and worker fixed effects.

TABLE 8
Human capital variance decomposition: within/between

	$\gamma_j^G \text{Exp}_{it}$	Within	Between
Var	0.050	0.022	0.028
%	100	45	55
	$\gamma_j^S \text{Ten}_{ijt}$	Within	Between
Var	0.015	0.008	0.008
%	100	50	50

Source: *Relação Anual de Informações Sociais* (RAIS) 1999–2014.

As a result this may change the relative importance of firm and worker heterogeneity in shaping wage inequality.

We compare the contribution of different determinants of wages between the standard model and our model using the following log wage variance decomposition:

$$\text{Var}(\log W_{ijt}) = \underbrace{\text{Cov}(\log W_{ijt}, \alpha_i)}_{\text{worker}} + \underbrace{\text{Cov}(\log W_{ijt}, \phi_j)}_{\text{firm}} + \underbrace{\text{Cov}(\log W_{ijt}, \gamma_j^S \text{Ten}_{ijt})}_{\text{worker/firm}} + \underbrace{\text{Cov}(\log W_{ijt}, \gamma_j^G \text{Exp}_{it})}_{\text{worker/firm}} + \underbrace{\text{Cov}(\log W_{ijt}, \lambda_t + u_{ijt})}_{\text{residual}}$$

where we can further decompose:

$$\text{Cov}(\log W_{ijt}, \gamma_j^S \text{Ten}_{ijt}) = \underbrace{\text{Cov}(\log W_{ijt}, \gamma_j^S \overline{\text{Ten}})}_{\textit{firm}} + \underbrace{\text{Cov}(\log W_{ijt}, \overline{\gamma^S} \text{Ten}_{ijt})}_{\text{worker}} + \text{cross terms}$$

and similarly for experience. $\overline{\text{Ten}}$ denotes the average tenure in the sample and $\overline{\gamma^S}$ denotes the average return to tenure.

Note that we assign each component of the decomposition either to firms or workers. Although this classification seems natural when looking at the contribution of worker and firm fixed effects, it is more controversial when it comes to assigning the role of tenure, Ten_{ijt}, and experience, Exp_{it}, as these are not only shaped by workers decisions but also hiring and firing decisions by firms. Introducing this dichotomy, even though somehow artificial, allows us to see if our model changes substantively the discussion about the role of firm and worker heterogeneity in shaping wage inequality.

Table 9 shows the contribution of each component in the standard model and in our model. Firstly, note that unobserved worker and firm wage premia explain 70% of the wage variance in both specifications. Overall, both specifications produce similar decomposition results with our decomposition implying marginally more prominent role for firm-specific capital (row 'Ten') compared to general human capital (row 'Exp') than the standard model. Results in Table 9 are also similar to the ones obtained by Lopes de Melo (2018), Engbom and Moser (2022), Alvarez *et al.* (2018) using different sample selections from RAIS data.[12]

[12]The variance of real log wages in our sample is slightly higher than in these articles as we focus on large companies.

TABLE 9
Log wage variance decomposition

	AKM		*Our model*	
	Cov	*%*	*Cov*	*%*
Log wage	0.815	100	0.815	100
Worker FE	0.410	50	0.407	50
Firm FE	0.151	19	0.162	20
Exp	0.023	3	0.010	1
γ_j^G			−0.016	−2
Exp_{it}			0.025	3
Ten	0.023	3	0.031	4
γ_j^S			0.002	0
Ten_{ijt}			0.036	4
Worker	0.456	56	0.449	57
Firm	0.151	19	0.162	18

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Both models include year fixed effects.

It is worth noting that, as anticipated from previous results, heterogeneity in the returns to experience works towards decreasing overall wage inequality (row γ_j^G) as the low returns to experience compensate the high firm-specific wage premia. However, this effect is rather small so the variation in the firm-specific experience premia virtually does not contribute to the overall wage variance. Looking at the breakdown between workers and firms (last two rows of Table 9) we notice that our decomposition produces almost exactly the same results as the standard model.

The literature on wage decompositions often takes as a point of interest an alternative decomposition which distinguishes the role of sorting, or generally covariance across regressors, as an important determinant of wage inequality. Results of this decomposition based on our model and data (not reported here) confirm the observations above. Also, in line with the findings from other studies (see e.g. Abowd *et al.*, 1999, Card *et al.*, 2013, Abowd, McKinney, and Schmutte, 2019) we find positive correlation between worker and firm fixed effects which implies positive sorting in the labour market. The value of this correlation in the standard model is 0.395, which is slightly larger than the results found in the aforementioned papers, and decreases to 0.369 in the heterogeneous model. The latter is expected as our model allows for sorting both based on the firm-specific wage premia and the firm-specific experience/tenure premia.

VI. Alternative specifications and robustness checks

Match quality

It is widely understood in the literature that the estimates of returns to tenure may be biased due to the confounding effect of match quality. Although allowing for firm-specific returns to experience and tenure is a step forward towards including more firm-worker heterogeneity in the model compared to AKM, the endogeneity of tenure may remain a problem for the credibility of our conclusions. Thus, in order to investigate robustness of our results, we apply the methods suggested in Abraham and Farber (1987) (AF), Altonji

TABLE 10

Accounting for match quality

	AF	*AS*	*Topel*
$\text{Corr}(\phi_j, \gamma_j^G)$	−0.431	−0.548	−0.547
$\text{Corr}(\phi_j, \gamma_j^S)$	−0.025	−0.060	0.287
$\text{Corr}(\alpha_i, \phi_j)$	0.338	0.355	

Source: *Relação Anual de Informações Sociais* (RAIS) 1999–2014.

and Shakotko (1987) (AS) and Topel (1991) (TO) to deal with the confounding effect of match quality.

AF propose controlling for completed job duration in order to avoid biased estimation of tenure coefficients. In order to implement the method one has to predict job duration for spells not completed in 2014. We predict these spells using a duration model similar to AF with experience, experience squared, years of education and dummies for each two digit occupation as explanatory variables.

In turn, AS suggest to instrument tenure by deviation of tenure from the mean over the job spell. In our case this would require instrumenting each tenure × firm ID interaction by a similar interaction involving deviation from mean tenure (on top of high-dimensional fixed effects and heterogenous experience returns), which makes the full IV estimation computationally infeasible.[13] Instead we find a middle ground between a full 2SLS estimation and a 'forbidden' regression (cf. Wooldridge, 2009), which would instrument tenure by tenure deviations in the first stage and then use the interaction of predicted values from the first stage and firm IDs in the second stage. Namely, we regress the endogenous interactions tenure × firm ID on all exogenous variables, including interactions of tenure deviations and firm IDs in the first stage, and then set the predicted values for tenure × firm ID to zero for observations that do not correspond to the chosen firm ID.[14]

TO method involves first using stayers to estimate $B_j \equiv \gamma_j^G + \gamma_j^S$, then estimating γ_j^G using $\log W_{ijt} - \hat{B}_j \text{Ten}_{ijt} = \gamma_j^G \text{Exp}_{0ij} + \phi_j + u_{ijt}$ where Exp_{0ij} denotes experience at the start of a job spell and, finally, estimating γ_j^S by $\hat{B}_j - \hat{\gamma}_j^G$. For reasons discussed above we also include time dummies in both stages.

Table 10 reports the results. The AF and AS estimates are similar to our main estimates reported in Table 3 and confirm fairly strong correlation between returns to experience and firm FEs.[15] The latter is also corroborated by Topel's model. However, TO model also predicts quite strong positive correlation between returns to tenure and firm FEs.

[13]At least using the *FixedEffectModels.jl* package. Though, we are not aware of any other package dealing with high-dimensional OLS or IV estimation more efficiently.

[14]This avoids the main complication of running the full 2SLS, namely storing predicted values for all tenure × firm ID interactions, which involves adding more than 11,000 non-sparse columns to the data, a task not feasible even with 5% firms in our data. Also, note that we cannot apply the IV methods that involve differencing as the estimates of the time-invariant FEs are of main interest.

[15]For the AS method we have managed to run full 2SLS for samples of 300 firms from the data (less than 3% of all firms). We obtained the average values (across five samples): $\text{Corr}(\phi_j, \gamma_j^G) = -0.579$, $\text{Corr}(\phi_j, \gamma_j^S) = 0.372$ and $\text{Corr}(\alpha_i, \phi_j) = 0.082$, though the estimates were quite variable between the samples, which may stem from differing strength of mobility across different sets of firms and the resulting differences in limited mobility bias.

As argued by Topel (1991) his method does not produce unbiased estimates of returns to tenure, but rather a lower bound on these returns. Thus, if the bias in the estimates is positively correlated with the firm FEs this may artificially generate positive correlation of the returns to tenure and the firm pay premia. Additionally, as the first step in the TO method uses only stayers it restricts the number of observations used in the estimation of B_j, which may contribute to this unexpected result as well. Thus, we take the positive correlation of the tenure returns and the firm FEs in TO model with a grain of salt and conclude from this section that our main results seem to be robust to accounting for the effect of match quality.

Limited mobility bias

Our estimated worker, firm fixed effects and firm-specific returns to experience and tenure are random variables, thus their sample variances and covariances will be biased (but consistent) estimators of the population values. As the bias may be particularly acute in datasets with limited transitions of workers between firms it has been coined limited mobility bias (see Andrews *et al.*, 2008). Kline *et al.* (2020) (henceforth, KSS) suggest a procedure to remove this bias. However, applying their procedure to our model with multiple firm-specific coefficients is computationally difficult.[16] Instead, in order to gauge importance of these biases in our estimation: (1) we analyze how the worker and firm effects variances and covariance are affected by KSS correction, after removing the effect of experience and tenure in the first step (which we coin 'reduced form KSS correction'), (2) we restrict the sample size to 'invoke' limited mobility bias and judge its direction and importance.

Reduced form KSS correction

In the first step we calculate $\log W^*_{ijt} = \log W_{ijt} - \hat{\gamma}^S_j \mathrm{Ten}_{ijt} - \hat{\gamma}^G_j \mathrm{Exp}_{it}$, where $(\hat{\gamma}^S_j, \hat{\gamma}^G_j)$ are the estimates of the coefficients from our heterogenous model or a homogenous model (i.e. coefficients constant in j), and in the second step we regress $\log W^*_{ijt}$ on time, worker and firm fixed effects.

The results in Table 11 show that both in the model with homogeneous effects of human capital and the model with firm-specific returns the KSS bias correction has almost no effect on the estimated variances and covariances of firm-specific coefficients, with very limited effect on moments involving worker-specific coefficients. The largest relative difference between the plug-in and KSS estimates is recorded for the variance of worker fixed effects, still the difference between bias-corrected and naive estimates does not exceed 11%. These results confirm the finding in Lachowska *et al.* (2020) that KSS corrections are of minor magnitude in relatively long panels (unlike the panel used in the original Kline *et al.*, 2020 article).

In order to provide additional evidence on the role of estimation error, in Appendix B we generate artificial data by assigning returns to experience/tenure to firms randomly and we estimate our model on these data. The results correctly detect lack

[16]Running KSS procedure just for a model with homogenous effect of experience and tenure takes around 2 hours and 80 GB of memory on two Intel Xeon 2.4 GHz cores.

TABLE 11
The effects of bias correction

	Linear model			*Quadratic model*		
	Plug-in	*KSS*	*% diff.*	*Plug-in*	*KSS*	*% diff.*
Panel A. Homogeneous effects of experience and tenure						
$Var(\phi_j)$	0.076	0.076	0.6	0.066	0.065	0.6
$\mathrm{Cov}(\alpha_i, \phi_j)$	0.065	0.066	−0.6	0.063	0.063	−0.5
$\mathrm{Var}(\alpha_i)$	0.357	0.323	10.6	0.368	0.340	8.5
$\mathrm{Corr}(\alpha_i, \phi_j)$	0.395	0.418	−5.7	0.405	0.425	−4.7
Panel B. Heterogeneous effects of experience and tenure						
$\mathrm{Var}(\phi_j)$	0.102	0.102	0.4	0.086	0.086	0.4
$\mathrm{Cov}(\alpha_i, \phi_j)$	0.071	0.071	−0.5	0.051	0.052	−0.6
$\mathrm{Var}(\alpha_i)$	0.362	0.332	9.1	0.365	0.338	7.8
$\mathrm{Corr}(\alpha_i, \phi_j)$	0.370	0.389	−4.9	0.289	0.389	−4.4

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) All models include year fixed effects; (iii) Estimates in column 'KSS' are bias-corrected using the procedure in Kline *et al.* (2020).

of correlation between firm-specific returns which reassures us further that the correlations we find in the data are unlikely to be driven solely by a small sample bias.

Restricted samples

Now we restrict the sample to 'invoke' limited mobility bias in two ways. Firstly, we know that the bias of correlations involving firm-specific coefficients is larger when firms connections (through workers mobility) are weaker. Thus, we follow the procedure in Andrews *et al.* (2012) and Bonhomme *et al.* (2023) and keep only a fraction of movers between firms in order to limit mobility, preserving the same set of firms across the samples. Secondly, the limited mobility bias is expected to be larger in shorter panels so we re-estimate the correlations of interest dropping final years and investigate how the correlations change with different panel lengths.

Table 12 shows the results. Notably all estimates obtained with dropping a fraction of movers are almost indistinguishable from the full sample estimates in Table 3, which again suggests that the limited mobility should not introduce significant bias to our findings. The results from shorter panels (last four columns of Table 12) confirm our earlier constatation that the limited mobility bias is a problem in short panels. The correlations obtained on a 3-year panel (1999–2001) differ considerably from full sample estimates—the negative correlation between firm fixed effects and returns to experience is visibly stronger and the correlation between firm fixed effects and returns to tenure has the opposite sign. This should serve as a warning sign for researchers estimating firm-specific returns to experience and tenure on very short panels. However, these estimates get relatively close to full sample values already with 6–9 years in the panel, which confirms that the limited mobility bias is really a short panel problem. Finally, it is worth noting that in line with findings in other studies the correlation between worker and firm fixed effects suffers from large downward bias in short panels, confirming the need for bias corrections advocated in Bonhomme *et al.* (2023).

Overall, these observations reassure us that the limited mobility bias should not be driving our main results.

TABLE 12
Correlation estimates on restricted samples

	Restricted mobility				*Restricted panel length*			
	20% movers	*40% movers*	*60% movers*	*80% movers*	*1999–2001*	*1999–2004*	*1999–2007*	*1999–2010*
$\mathrm{Corr}(\phi_j, \gamma_j^G)$	−0.512	−0.512	−0.511	−0.509	−0.780	−0.526	−0.462	−0.461
$\mathrm{Corr}(\phi_j, \gamma_j^S)$	−0.086	−0.086	−0.085	−0.085	0.142	−0.147	−0.110	−0.104
$\mathrm{Corr}(\alpha_i, \phi_j)$	0.366	0.367	0.368	0.369	0.041	0.143	0.285	0.344

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) First four columns present estimates with keeping XX% of movers and full panel; (iii) Last four columns use only data from selected periods and keep all movers in these periods.

TABLE 13
Heterogeneous coefficients and cumulative returns: nonlinear models

	Mean	*SD*	*2 years*	*5 years*	*10 years*
Panel A. Quadratic model					
Exp	0.053	0.017	0.102	0.243	0.441
Exp^2	−0.0009	0.0003			
Ten	0.030	0.060	0.055	0.114	0.153
Ten^2	−0.001	0.092			
Panel B. Cubic model					
Exp	0.078	0.028	0.147	0.337	0.577
Exp^2	−0.002	0.001			
Exp^3	0.00002	0.00003			
Ten	0.042	0.113	0.070	0.127	0.147
Ten^2	−0.004	0.441			
Ten^3	0.0001	1.674			

Notes: (i) Source: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) 2 years, 5 years, and 10 years indicate different corresponding years of cumulative returns to tenure or experience.

Nonlinear models

As mentioned above, we would normally expect diminishing returns to experience and tenure, thus the standard specification should include nonlinear terms. In this section we add squared and/or cubed experience and tenure to the model and show that our results above are confirmed in this extended model.

The results from the quadratic model and the cubic model are given in Table 13 where we report means and standard deviations of the estimated coefficients as well as mean cumulative returns from 2, 5 and 10 years of experience and tenure. The estimates from the cubic model are highly variable, which suggests that the length of our panel (16 years) does not allow reliable estimation of higher order curvature of individual experience profiles. This is also confirmed by looking at plots of individual experience profiles (not reported here) with many profiles showing decreasing or explosive patterns.[17] Thus, we focus our discussion on the estimates from the quadratic model which look much more reliable.

[17] We have also estimated a model with a three-piece linear spline for experience and tenure. As argued above, identification of this model is trickier and we are able to identify coefficients for only around 9,000 firms. The results are presented in Figure D3 in Appendix D and confirm our main observations.

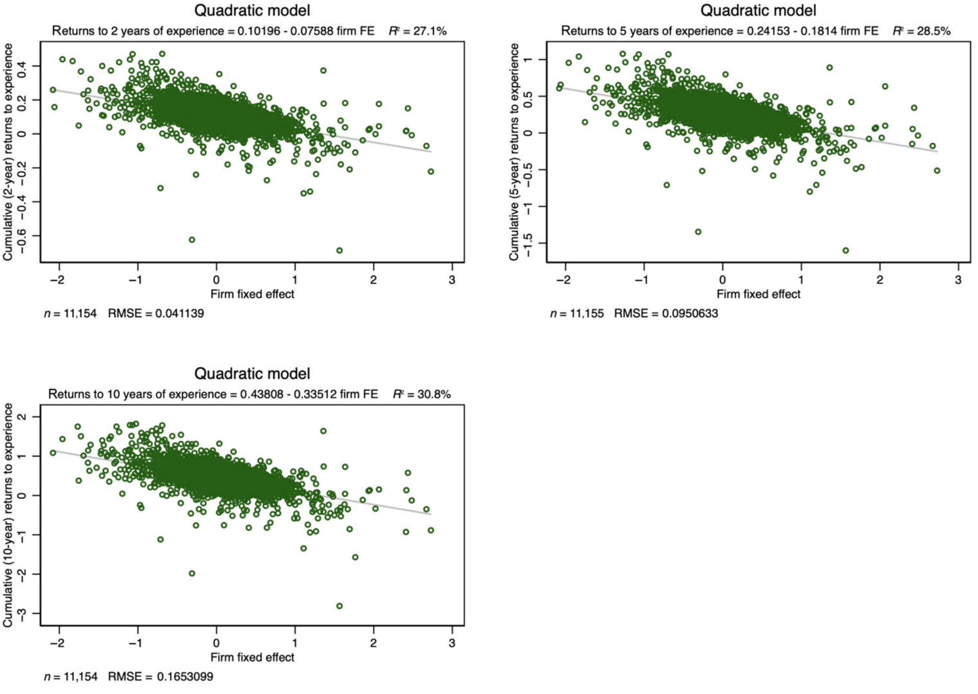

Figure 9. Cumulative returns to 2, 5 and 10 years of experience vs. firm fixed effects: quadratic model.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

The estimates confirm that the returns to tenure are more variable than the returns to experience. As expected, there are diminishing returns to experience and tenure, with 5 years of tenure yielding a 11.4% return for the quadratic model, which is lower than the return found by Topel (1991): 17.9%, and Buchinsky *et al.* (2010): 29%, but higher than the estimate in Altonji and Williams (2005): 9.7%.[18] Figure 9 shows that the negative relationship between the returns to experience and the firm-specific wage premia occurs also in the nonlinear models. Thus, our findings above cannot be explained by misspecification of the linear model in (1).

In Figure 10, left panel, we plot mean values of the firm fixed effects by age and education level. We can see that there is positive sorting based on firm wage premia with more educated workers employed by companies offering higher premia for all age groups. The middle and right panel plot the experience and tenure component of the log wage equation for different age and education groups. As the differences between lines here can be attributed largely to differences in firm-specific experience premia, the middle panel shows that there is negative sorting of workers on experience premia up to age 40 with more educated workers being employed for companies offering lower returns to experience. This confirms our previous observation that differences in experience premia act towards decreasing wage inequality. The sorting is less evident above age 40, though

[18]Dustmann and Meghir (2005) estimate 12% for skilled workers and 20% for unskilled workers.

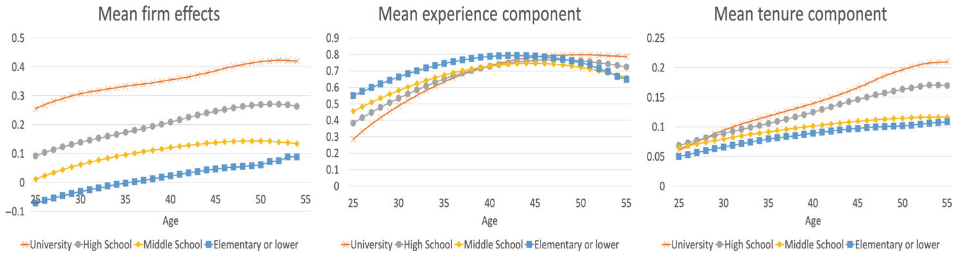

Figure 10. Mean fixed effects, mean experience and tenure components by age and education.
Notes: (i) The mean experience component is calculated as the sample average over $\hat{\gamma}_j^G \text{Exp}_{it} + \hat{\gamma}_{j,2}^G \text{Exp}_{it}^2$, where $\hat{\gamma}_j^G$ and $\hat{\gamma}_{j,2}^G$ are estimates from the quadratic model; (ii) The mean tenure component is calculated similarly; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

this may be a result of imprecise estimation of the curvature of firm-specific experience profiles mentioned above.

The right panel of Figure 10 shows that the average value of firm-specific human capital is similar across education groups until age 30 but diverges above that age, with educated employees in the age group 50–55 having significantly higher firm-specific human capital component than non-educated employees. Note that in the case of tenure profiles, the differences between the lines cannot be interpreted as only a result of selection based on different firm-specific returns to tenure but can also be caused by different average tenure lengths for educated and non-educated workers. In fact we find that more educated workers have higher average tenure at older ages, which manifests itself with higher value of the specific human capital component $(\hat{\gamma}_j^S \text{Ten}_{ijt} + \hat{\gamma}_{j,2}^S \text{Ten}_{ijt}^2)$ even though the composition of returns to tenure, $(\hat{\gamma}_j^S, \hat{\gamma}_{j,2}^S)$, is quite similar in all education groups. Thus, it is the diverging worker histories across education levels, rather than diverging selection patterns, that explain the divergence of profiles in the right panel in Figure 10.

Potential experience

As mentioned above we use actual experience in our empirical investigation. However, as Brazilian labour market includes a large informal sector (see e.g. Dix-Carneiro and Kovak, 2019) we expect that, for many workers in our administrative dataset, the time spent outside of the panel corresponds to spells of informal employment, thus using potential experience may give a better approximation to actual labour market experience than experience calculated from the RAIS panel.

The disadvantage of using potential experience in our regression is that we cannot include year fixed effects at the same time because of collinearity. As demonstrated in Figure 1, Brazil experienced rapid wage growth during the sample period. Thus, the estimates of experience and tenure premia in this section will include macroeconomic trends and are higher than the estimates obtained using actual experience in the main discussion. Whether one should include year effects when estimating returns to human capital is a point of discussion. For example, if growth in real wages in the economy is fuelled by increased productivity due to learning-by-doing, it seems natural to assign the real wage growth to returns to experience or tenure.

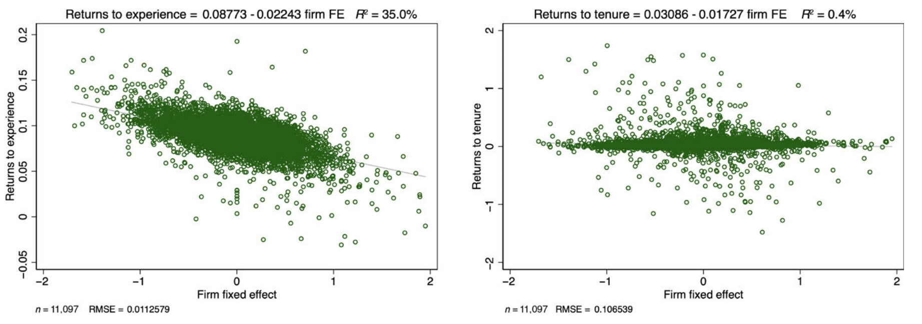

Figure 11. Heterogeneous coefficients: returns to potential experience (left) and tenure (right) vs. firm fixed effects.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

The correlation between potential experience and Exp is quite high, 0.972. Additionally, the model estimates obtained with potential experience are highly correlated with estimates obtained using Exp: correlation coefficient of 0.96–0.97 for worker and firm effects, 0.93 for returns to tenure and 0.86 for returns to experience. Figure 11 shows that, if anything, replacing actual experience with potential experience leads to a slightly stronger inverse relationship between the firm-specific returns to experience and the firm wage premia. We obtain both slightly steeper line and higher R^2 here than in Figure 2. Also, these results confirm lack of any visible relationship between the returns to tenure and the firm wage premia. More detailed results for the model with potential experience are shown in Table D1 and Figure D4 (see Appendix D).

Firm-year effects

Snell *et al.* (2018) point out that including firm-year effects could remove bias from estimating tenure returns as it controls for comovement of firm employment and firm wages. Possibly such comovement may also affect our estimated correlations. For the purpose of investigating the robustness of our results to this mechanism we re-estimate our model making the year dummies firm-specific.

Table 14 shows that including firm-year effects leads to a correlation between firm fixed effects and returns to experience of −0.533, which is actually a slightly lower value than in our baseline model. Correlation of firm FEs with tenure coefficients flips sign compared to the value from the main model (−0.085) but is still very close to zero. Overall, we conclude that introducing firm-year fixed effects into our model has little effect on our findings.

Separate estimates for services and production

The overall firm graph in RAIS is rather weakly connected, with global connectivity measure of 0.02 (see Appendix A). As a result, as argued by Jochmans and Weidner (2019), the firm fixed effects and firm premia may be estimated with little precision. On the other

TABLE 14

Heterogeneous coefficients: model with firm-year fixed effects

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Worker FE	0.000	0.596	0.274	
Firm FE	0.077	0.186		0.274
Exp	0.019	0.008	−0.533	0.044
Ten	0.015	0.026	0.020	−0.015

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

TABLE 15

Heterogeneous coefficients: separate estimates for two industries

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Panel A. Services				
Worker FE	0.000	0.585	0.306	
Firm FE	0.207	0.310		0.306
Exp	0.010	0.011	−0.437	0.175
Ten	0.013	0.044	−0.130	−0.005
Panel B. Production and construction				
Worker FE	0.000	0.642	0.405	
Firm FE	0.113	0.336		0.405
Exp	0.013	0.009	−0.575	−0.154
Ten	0.014	0.026	−0.036	−0.061

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

hand, the intra-industry firm graphs are rather well connected with global connectivity of 0.116 for services (still 0.014 measure for production and construction). Thus, as a robustness check to our main results we re-estimate our model separately for service and production and construction sectors.[19]

Comparing Table 15 to Table 4 we do not see any stark differences in estimated mean wage returns and correlations between experience/tenure returns and firm fixed effects. If anything, we obtain a slightly weaker correlation between the tenure returns and the firm fixed effects in the service sector (−0.130 vs. −0.134 in Table 4), though the magnitudes of both estimates are minor, and a slightly stronger correlation between the returns to experience and the firm fixed effects in the production sector (−0.575 vs. −0.526 in Table 4). However, none of these differences is large enough to support the claim that our main estimates are affected by weak connectivity of the employer–employee network. Graphical correlations for both sectors (see Appendix D) also support this conclusion.

[19]We choose the largest connected components for each sector. For services this component includes 96% of firms in the sector and 99.9% of workers. For production and construction the corresponding numbers are 99.1% and 99.99%.

VII. Discussion

In this section we discuss our findings on the firm-specific returns to experience and tenure in the view of existing theories of the labour market.

Returns to tenure

Heterogeneity in returns to tenure across firms can be well understood based on the human capital theory (Becker, 1962, Rosen, 1976). Based on this theory, significant main contributors to heterogeneous returns to tenure include differences in training opportunities across different firms, as well as the impact of these differences on employee productivity gains (Hutchens, 1989). The (weak) negative correlation between the firm-specific pay premium and the firm-specific return to tenure can then be understood as an empirical regularity meaning that firms offering higher starting wage premia also offer poorer training opportunities.

Alternatively, the latter correlation can be attributed to implicit contracts between employers and employees (Lazear, 1981). The implicit contract stipulates that entrants will be paid a wage that is lower than the value of their marginal product at the beginning of the contract but higher than the value of their marginal product at the end. Assuming all other factors are similar, if the present value of the wage paid is the same for both options, there is no difference in the attractiveness to employees of the firm offering the implicit contract and the firm paying a wage equal to the value of the worker's marginal product. The implicit contract means that the company uses the strategy of deferred compensation to reward employees, and this approach can effectively solve the agency problem between the employer and the employee. Note that under the agency theory interpretation, the returns to tenure are not really measuring returns to human capital but rather indicating the strength of the agency problem.

Lazear's agency theory can also provide potential explanation for the patterns of correlation across different firm types. Firstly, it is more advantageous for companies with a predominantly white-collar workforce to offer implicit wage contracts with backloaded wage payments according to predictions of agency theory. As their efforts have a stronger positive effect on improving firm performance, white collar employees typically have greater mobility. Therefore, it is essential to link white collar employees through implicit contracts in order to lower their turnover rate and maintain their loyalty to the company. This explains higher absolute values of $\mathrm{Corr}(\phi_j, \gamma_j^S)$ among 'white collar' firms.

Secondly, regarding the size of the firm, the increase in firm size usually increases the agency costs of the firm as large firms have more departments and more employees (Booth and Frank, 1996). While large firms need to deal with more severe agency problems, small firms can more efficiently resolve the agency problems caused by hidden information and hidden behaviour by rewarding individual performance (Zenger, 1994). Hence, large firms have to backload wage payment more, a finding consistent with $\mathrm{Corr}(\phi_j, \gamma_j^S)$ growing in absolute value with firm size observed in our data.

Thirdly, when it comes to the firm age, old companies are in better position to guarantee the fulfilment of deferred compensation provided in the implicit contract than young companies. One of the main reasons is that longer functioning firms usually care more about their reputation and the breach of the implicit contract will have a negative impact on their reputation (Hörner, 2002). Another major reason is that the survival rate of young firms and startups is at a low level, and if they fail, they will lose the ability to fulfil their implicit contracts. According to the U.S. Bureau of Labor Statistics (BLS), about 20% of start-ups fail within the first 2 years of opening, 65% fail within the first 10 years, and only 25% of start-ups make it 15 years or more. These explain well one of our findings that $Corr(\phi_j, \gamma_j^S)$ is higher in absolute value among older firms.

Although the observed correlation patterns seem to match the agency theory, it is clear that the correlation between tenure returns and firm pay premia is rather weak. On one hand this may suggest that the wage effects generated by the agency problem are small, either due to low importance of this problem in actual wage setting or inability to enforce implicit contracts needed for these effects to occur. On the other, this finding may be specific to our Brazilian data. In comparison to developed nations, Brazil, a significant emerging economy, has a less regulated labour market and a relatively lower cost of terminating employees (Prates and Barbosa, 2020). Such labor market characteristics allow employers to deviate from the implicit contract with employees relatively freely or at low cost, and to capture more benefits through early termination. At the same time, the relatively immature market and the relatively inadequate laws and regulations create greater challenges for the survival rate of startups, which in turn affects the ability of firms to fulfil implicit contracts (Ponczek and Ulyssea, 2022). All these may create an environment in which the implicit contracting embedded in the agency theory may be harder to sustain, thus weakening the predicted effects.

Returns to experience

Heterogeneity of returns to experience can be understood using the skill weighting approach proposed by Lazear (2009). Within this framework each year of experience is a bundle of skills and different firms value elements of this bundle differently. Thus, firms may attract different workers in terms of their experience composition and thus remunerate their experience differently. Here two explanations are possible. Firstly, if we assume that workers with the same number of years of experience possess exactly the same skill set, they may still end up in companies valuing these skills differently (e.g. due to search frictions) and thus be remunerated differently for their experience. Secondly, if two workers with the same experience have different skill sets, they may sort themselves to different firms depending on how these firms pay for their dominant skills, which in turn may generate heterogenous returns to experience across firms if different skills are remunerated differently in the market. Note that the latter explanation would mean that our heterogenous returns to experience really disguise heterogeneity of experience pools across firms. Unfortunately, without data on specific skills possessed by workers with the same years of experience we cannot empirically distinguish one explanation from the other.

It is more difficult to find theoretical background for our main finding, namely the strong negative correlation of experience returns and firm pay premia. In view of Lazear's skill weighting approach, this can be just interpreted as a pattern in the characteristics of the firms—the firms that put more weight on well-remunerated skills also happen to offer low pay premia, especially among ‘blue collar’, smaller and older firms. However, this interpretation seems somehow unsatisfactory and a more elaborate theory explaining how these patterns arise in a labour market equilibrium would be desirable.

VIII. Conclusion

We extend the standard two-way fixed effects model of wage formation by allowing the returns to experience and tenure to vary between firms and estimate the parameters using a large matched employer–employee dataset from Brazil. We provide new estimates of the return to tenure assuming that workers sort themselves based on differential wage contract terms with respect to experience and tenure premia, obtaining an average return to 5 years of tenure equal to 11.4%. We document the variation in firm-specific experience and tenure premia and find that returns to tenure are not strongly related to firm wage premia (i.e. firm FEs), returns to experience are strongly negatively correlated with firm wage premia, the relationship between firm wage premium and return to experience is stronger for ‘blue collar’ firms.

As argued by Dustmann and Meghir (2005) transitions in and out of employment and sorting of workers based on match quality, in general, lead to endogeneity of experience in the standard model. Thus, they recommend to identify the effect of experience by using only displaced workers. As RAIS data allows us to track the firms over time and lists the reason for termination of the employment relationship we could potentially identify displaced workers in our data. Moreover, we define tenure as the time spent with a current employer. However, as shown by Buhai *et al.* (2014) not only nominal tenure matters for wages but tenure *relative* to other workers is also an important determinant of pay. It would be interesting to investigate heterogeneity in relative tenure using our data. We leave both these extension for future research.

Appendix A: Connectivity of employer–employee network in RAIS

As recommended by Jochmans and Weidner (2019) we measure connectivity by the smallest non-zero eigenvalue of the (normalized) Laplacian matrix of the graph. We consider both the bipartite employer–employee network and the firm network, that is, projection of the bipartite network on firm nodes, and distinguish services and production and construction sectors.

Table A1 shows, in line with observations for other matched employer–employee datasets, that the bipartite network is rather weakly connected and contains bottlenecks that will prevent precise estimation of the worker effects. As we do not really use

TABLE A1

Smallest non-zero eigenvalue of the normalized Laplacian matrix

	Bipartite	*Firm*
All	0.000617	0.019733
Services	0.000479	0.116439
Production and construction	0.000156	0.014386

individual effects in our analysis, but rather their firm averages, this weak connectivity is not of major concern. The firm network is much better connected, especially if we restrict ourselves to sectoral sub-networks. The latter suggests that the firm fixed effects and firm-specific coefficients may be estimated with much better precision if we perform within-sector estimation.

Appendix B: Role of estimation error

Although our sample contains millions of observations, the firm effects as well as the firm-specific experience and tenure coefficients are subject to estimation error. The estimation error in these coefficients will usually be correlated so this may partly drive our results. In order to appreciate this point, ignore the worker fixed effects and tenure coefficients and consider a highly stylized environment in which all firms share the same value of the fixed effect and the effect of experience. Additionally, assume that each firm's workforce is an independent sample drawn from the population of all workers. In such an environment, we can obtain an estimate of the fixed effect (i.e. a constant term) and the return to experience for each firm by running firm-specific regressions. These coefficients for different firms can be seen as different draws from the sampling distribution of the estimators. Thus, the correlation between the *estimated* firm fixed effects and the *estimated* returns to experience will merely pick up the correlation between the estimators, and will be non-zero even though the correlation between the *true* fixed effects and the *true* returns to experience is zero.

Although our setup is far from this stylized environment, it may still be the case that the significant correlation between firm wage premia and firm-specific returns to

	Mean	*SD*	*Corr (·, firm FE)*	*Corr(·, worker FE)*
Worker FE	0.000	0.611	0.363	
Firm FE	0.100	0.319		0.363
Exp	0.013	0.009	0.018	0.019
Ten	0.016	0.029	–0.003	–0.013

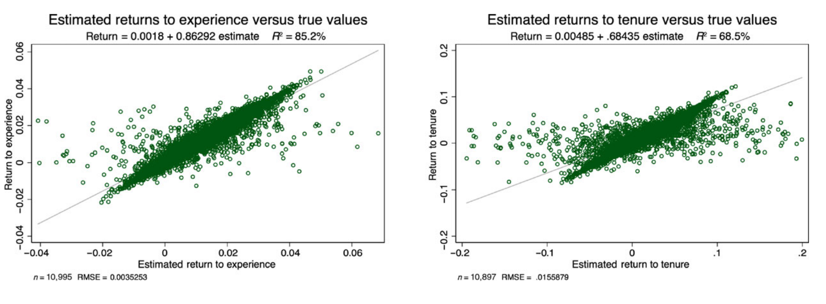

Figure B1. Estimates with randomly generated firm-specific returns to experience and tenure.
Notes: (i) The estimates were obtained using the same methods as the ones in Table 3; (ii) The data on wages was generated assuming that firm-specific experience and tenure effects are drawn independently from normal distributions with the same means and standard variations as those in Table 3; (iii) The outliers have been removed from the figures [Colour figure can be viewed at *wileyonlinelibrary.com*]

experience are driven partly by the estimation error. In order to investigate this possibility, we perform a simple exercise in which we generate artificial wages using our data and our estimates of the worker and firm fixed effects, year effects and the sample variance of the residuals. However, instead of the estimated firm-specific experience and tenure premia we use randomly generated numbers from a normal distribution keeping the same mean and variance of the estimates.

Figure B1 shows that estimating the model on the artificial data produces correlations between the estimated returns to experience and tenure and fixed effects that are close to zero in line with our imposed randomness of the firm-specific coefficients. This suggests that the correlated estimation error plays a minor, if any, role in generating sizeable correlations in our RAIS data (cf. Table 3). Additionally, our exercise reveals that the experience coefficients are likely to be estimated with more precision than the tenure coefficients.

Appendix C: Additional robustness checks

As mentioned in the main text, we restrict our sample to firms with 100 employees or more. As this may raise concerns about external validity of our results, here we relax this restriction and include firms with more than 50 employees. Additionally, we only require at least five movers per firm during the sample period, compared to 10 in the main text (this leaves 91% of firms and 99% of workers from the original sample). This increases the number of firms in the estimation sample to 24,542, the number of workers to 13,545,621 and the number of worker-year observations to 74,466,730.

Table C1 reports the main statistics for the estimated heterogenous coefficients on this extended sample. Both the mean values and correlations are very similar to the ones displayed in Tables 3 and 13, with the only notable difference being a slightly higher estimated mean return to 5 and 10 years of tenure. It is worth noting that the current sample, including smaller firms and weaker restrictions on mobility across firms, is more prone to suffering from mobility bias, so the results in this section are reassuring, in that they suggest that mobility bias does not seem to play an important role in our exercise.

TABLE C1

Heterogeneous coefficients, firms with 50+ employees

	Mean	SD	Corr(·, firm FE)	Corr(·, worker FE)
Worker FE	0.000	0.586	0.366	
Firm FE	0.129	0.321		0.366
Exp	0.012	0.009	−0.495	−0.031
Ten	0.017	0.038	−0.070	−0.027
		Quadratic model		
		2 years	5 years	10 years
Mean ret. to Exp		0.100	0.238	0.432
Mean ret. to Ten		0.060	0.129	0.188

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia); (iv) 2 years, 5 years and 10 years indicate different corresponding years of cumulative returns to tenure or experience.

Appendix D: Additional graphs and tables

TABLE D1
Heterogeneous coefficients: potential experience

	Mean	*SD*	*Corr(·, firm FE)*	*Corr(·, worker FE)*
Worker FE	0.000	1.065	0.149	
Firm FE	0.108	0.360		0.149
Exp	0.089	0.011	−0.567	0.112
Ten	0.023	0.029	0.081	−0.0005

Notes: (i) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999–2014; (ii) Corr(·, firm FE) displays the pairwise correlation coefficients between firm fixed effect and the rest of variables (worker fixed effect, firm-specific experience and tenure premia); (iii) Corr(·, worker FE) displays the pairwise correlation coefficients between worker fixed effect and the rest of variables (firm fixed effect, firm-specific experience and tenure premia).

TABLE D2
Summary statistics for subpopulations

	Mean	*SD*	*Min.*	*Max.*
Panel A. Service				
Wage (in 2010 Reals)	20.41	32.56	0.42	1,739.82
Tenure (in years)	4.72	5.63	0	45
Experience (in years)	19.94	10.44	0	45
Years of education	9.59	3.11	0	21
NT	19,682,990			
J	6,987			
N	3,960,797			
Panel B. Production and construction				
Wage (in 2010 Reals)	25.01	37.95	0.42	1,557.26
Tenure (in years)	5.77	6.75	0	45
Experience (in years)	19.51	10.38	0	45
Years of education	9.11	3.48	0	21
NT	32,145,912			
J	5,722			
N	5,792,124			
Panel C. White collar firms				
Wage (in 2010 Reals)	38.41	51.11	0.42	1,739.82
Tenure (in years)	6.79	7.68	0	45
Experience (in years)	20.4	11.2	0	45
Years of education	11.49	2.44	0	21
NT	19,522,089			
J	2,805			
N	3,734,432			

TABLE D2
Continued

	Mean	*SD*	*Min.*	*Max.*
Panel D. Blue collar firms				
Wage (in 2010 Reals)	12.11	17.88	0.42	1,739.82
Tenure (in years)	6.80	7.68	0	45
Experience (in years)	17.34	9.99	0	45
Years of education	6.43	3.44	0	21
NT	12,660,505			
J	2,805			
N	6,906,558			
Panel E. Small firms				
Wage (in 2010 Reals)	16.18	25.84	0.42	1,421.83
Tenure (in years)	4.69	5.26	0	45
Experience (in years)	19.80	10.64	0	45
Years of education	8.80	3.21	0	21
NT	5,427,844			
J	3,728			
N	1,798,672			
Panel F. Medium firms				
Wage (in 2010 Reals)	17.87	27.78	0.42	1,491.46
Tenure (in years)	4.67	5.35	0	45
Experience (in years)	19.50	10.57	0	45
Years of education	9.05	3.13	0	21
NT	10,382,180			
J	3,728			
N	3,404,645			
Panel G. Large firms				
Wage (in 2010 Reals)	23.44	36.68	0.42	1,739.82
Tenure (in years)	5.19	6.37	0	45
Experience (in years)	18.92	10.43	0	45
Years of education	9.48	3.28	0	21
NT	48,711,640			
J	3,733			
N	9,814,992			
Panel H. Young firms				
Wage (in 2010 Reals)	19.53	29.18	0.4	1,708.96
Tenure (in years)	4.51	5.68	0	45
Experience (in years)	19.25	10.54	0	45
Years of education	9.16	3.23	0	21
NT	17,572,016			
J	5,728			
N	4,734,904			
Panel I. Old firms				
Wage (in 2010 Reals)	22.83	36.48	0.4	1,739.82
Tenure (in years)	5.27	6.28	0	45
Experience (in years)	19.02	10.45	0	45
Years of education	9.42	3.26	0	21
NT	46,949,648			
J	5,490			
N	9,113,628			

Source: (i) *Relação Anual de Informações Sociais* (RAIS) 1999–2014. (ii) J, N, and NT denote the number of firms, the number of employees and number of observations in the RAIS, respectively.

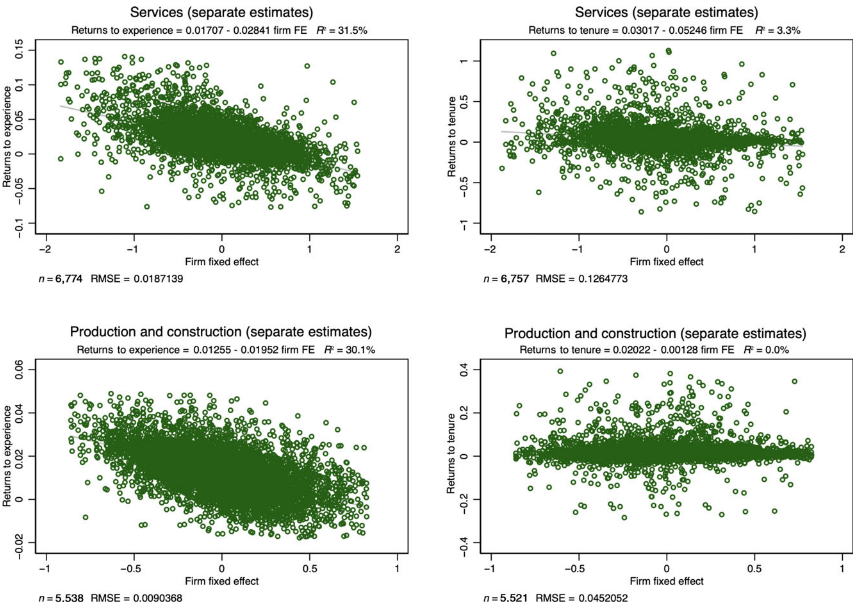

Figure D1. Returns to experience/tenure vs. firm fixed effects: separate estimates for two industries.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999-2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

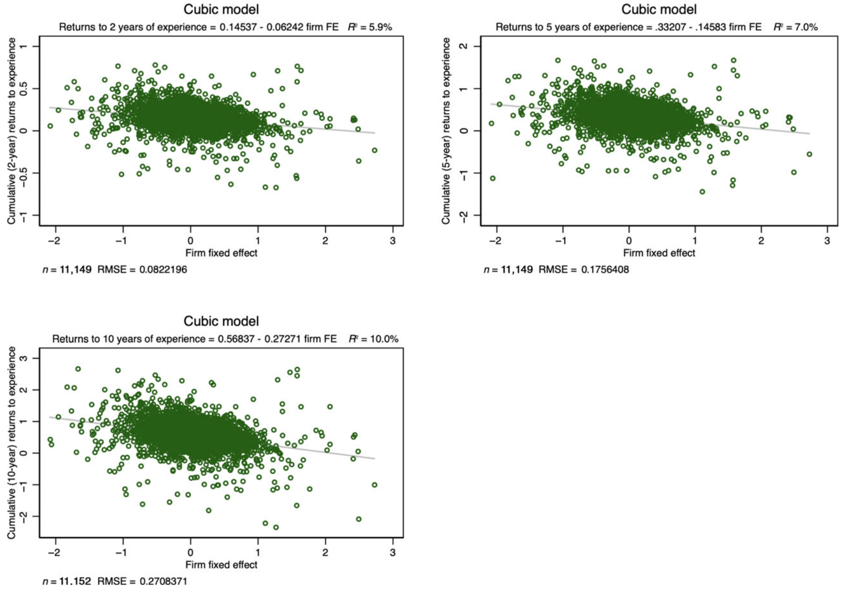

Figure D2. Cumulative returns to 2, 5 and 10 years of experience vs. firm fixed effects: cubic model.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999-2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

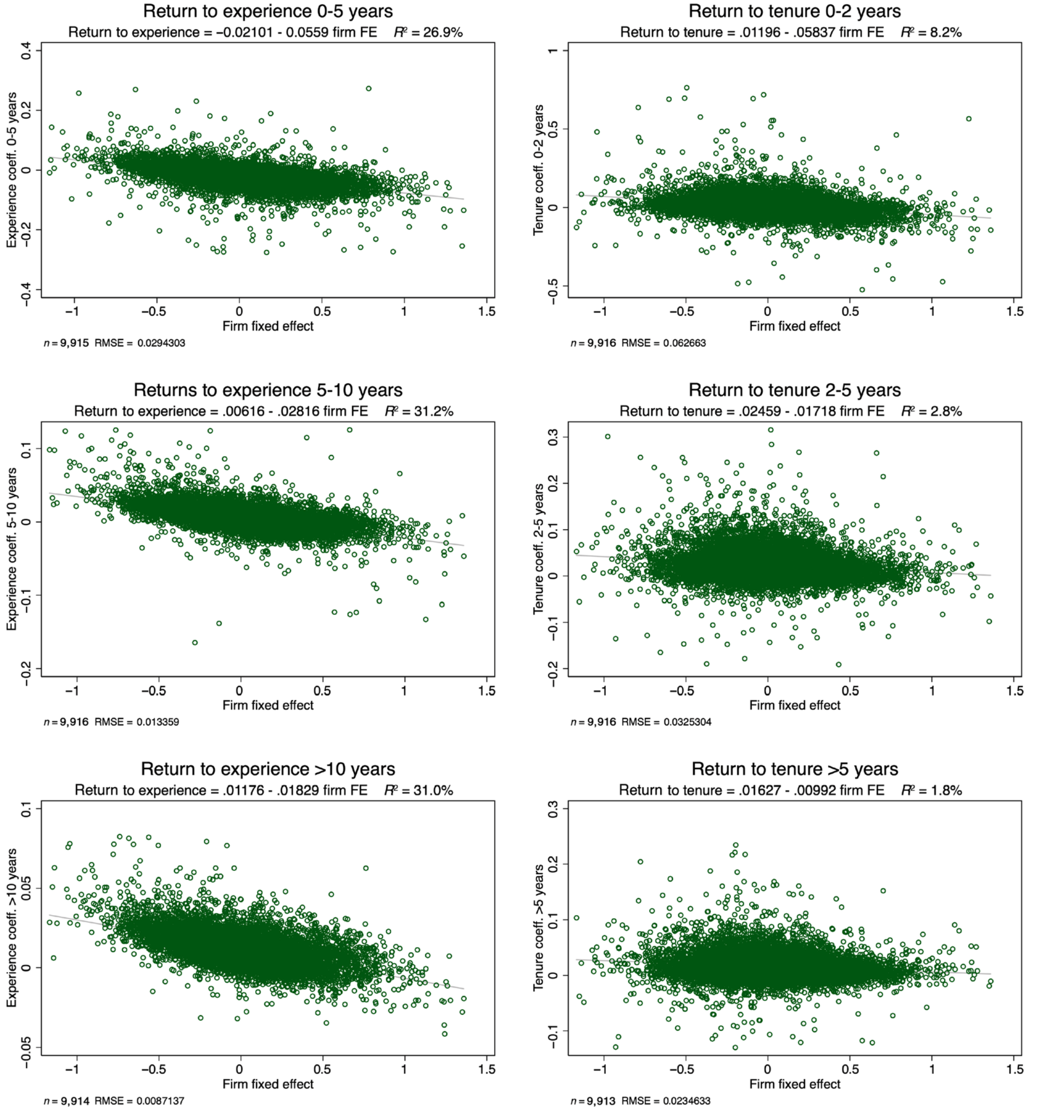

Figure D3. Returns to experience/tenure vs. firm fixed effects: 3-piece linear spline.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from a model with 3-piece linear spline for experience and tenure; (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999-2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

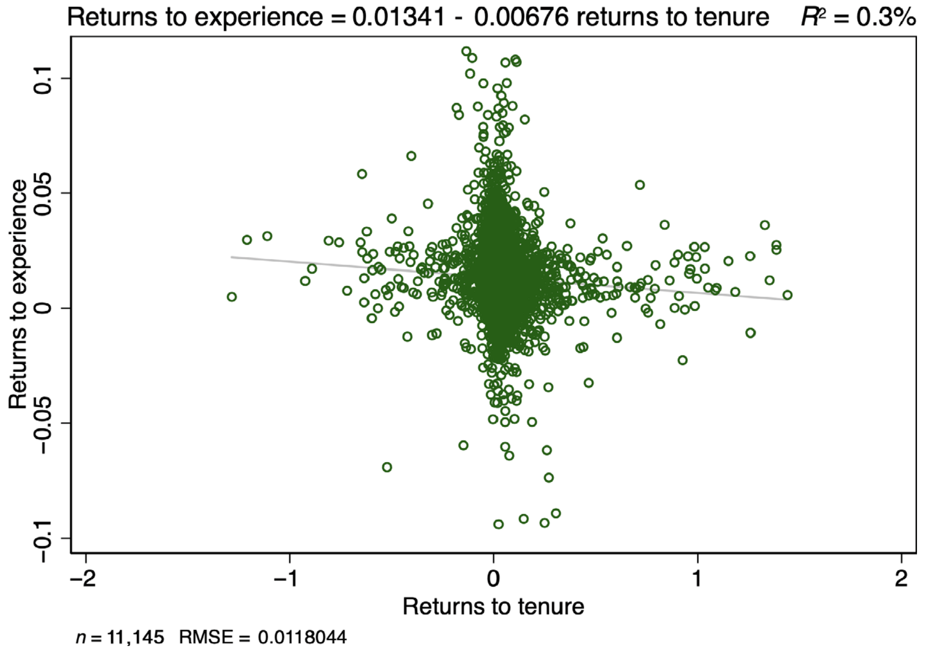

Figure D4. Heterogeneous coefficients: return to potential experience vs. return to tenure.
Notes: (i) Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1); (ii) Outliers are excluded; (iii) *Source*: *Relação Anual de Informações Sociais* (RAIS) 1999-2014 [Colour figure can be viewed at *wileyonlinelibrary.com*]

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