Firms Determinants on Wage Growth*

Caio Bloise

Insper
caiorcb@al.insper.edu.br

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Abstract

I run a two-way fixed effects model to see the role of firms fixed-effects in the wage growth determination. I rely on a unique dataset from Brazil (*RAIS*), which allows us to identify employee-employer for all formal jobs and firms in São Paulo, the largest state of Brazil. I find that, in general, firm's fixed-effects start to be decisive to earnings growth only above the 25th percentile. I also see a flat pattern in age, indicating that when individuals get older, their earnings growth starts to be lower than younger individuals. When the analysis is segmented by level of education, I find that individuals with less than high school (LHS) show an earnings growth only above the 50th firm percentile and below individuals with high school (HS). Still, surprisingly, high-school individuals show an earnings growth higher than those above high school (AHS). I also find that, woman and black workers experience lower wage growth than the benchmark exercise. When the focus is only on job-stayers, workers show a lower wage growth than individuals who experienced job-to-job transitions.

Keywords: wage growth, labor-market, AKM, linked employer-employee data, firm dynamics.

J.E.L. codes: To fill

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1 Introduction

Wage determination is one of the main questions that puzzles economists. This literature has been growing, mainly after the seminal paper of Abowd et al. (1999) (henceforth, AKM), which explores the role of firms and persons own characteristics on the determination of wage level. Although the AKM model has been widely used to study wage determinants, little is known about the binary indicators (person and firm-fixed effects) and their role in earnings growth.[1] Most of this gap has been filled on the theoretical side, as in Postel–Vinay and Robin (2002), Cahuc et al. (2006), Bagger et al. (2014) and Ozkan et al. (2023).

In this paper, I revisit the estimation of the AKM model, but where the dependent variable is wage growth (instead of wage level), as in Sørensen and Vejlin (2011) and Gregory (2021), extending their analysis to a unique dataset of matched employer-employee (*RAIS*) that allow us to inspect the determinants of wage growth to developing economies. The matched employer-employee dataset contains all registers about formal firms and workers in Brazil, which allows the identification of person-fixed effects and firms' wage premiums. After estimating the set of fixed effects, I use them to rank firms from the most productive to the least productive ones and use the coefficients on the AKM regression to predict earnings growth for different ages and levels of education according to firms' rank.

I find that differently from the results described by Gregory (2021)[2], the firm fixed-effects only begin to be decisive to earnings growth from the 25th percentile and above. After five years, individuals in that percentile show an earnings growth of 0.16%. For individuals in the 50th rank of firms fixed-effects, the sum of predictive earnings is equal to 0.53%. When I consider the highest percentile of the firms analyzed, the 75th and 90th, I see a higher wage growth of 0.90% and 1.34%, respectively. However, when analyzing the accumulated earnings for workers in the bottom percentile firms, I find a wage decline of 0.32%. Therefore, firms in the bottom percentile contribute to a wage decline instead of a wage growth.

I also find a flat pattern when workers get older. In other words, older workers show less steep earnings growth compared to younger individuals. For thirty years old individuals, at the 90th percentile, accumulated earnings grow 1.28% while at the 75th percentile, the change is estimated at 0.83%. In the last percentile analyzed, the earnings decline was

[1] In this paper, I will use wage and earnings interchangeably.

[2] In her firm rank percentile, wage growth starts to happen at 10th percentile.

about 0.40%. Thirty-five years old workers display the same pattern. Individuals in the most productive firms show a sum of predicting earnings of 1.25%, while the workers in the 10th percentile show a wage decline of 0.42%.

When I split the results by levels of education, I find that individuals with high school (HS) education show higher earnings growth than individuals with less educated workers, especially those without high school degrees (LHS). The same pattern occurs in comparison of the above high school (AHS) with LHS individuals, but interestingly, I cannot see the same pattern with AHS and HS workers. For LHS individuals, the earnings growth in the 90th percentile is about 1.03%, while for HS and AHS individuals, 1.60% and 1.14%, respectively. Again, in the 10th percentile, the wage growth is a wage decline of 0.99%, 0.52% and 1.10% for LHS, HS and AHS.

I also segment the results by gender and race. The wage growth for black and female workers is lower than the total sample. The wage growth for female workers is about 0.79%, while for black workers it is 0.87% for firms in the 90th percentile of productivity. On the other hand, for those in the bottom percentile, the wage decline is about 0.98% and 1.49%, respectively. Hence, black and female workers experience lower wage growth than in the full sample. More concerning is that black workers experience a larger wage decline than the full sample estimate.

The results described above care about the wage growth for workers who stayed in the same firm or had job-to-job transitions. Following Gregory (2021), I analyze how firms determine wage growth for only job-stayers. Overall, the results show a lower wage growth than in the previous models. The earnings growth for younger individuals in the top firms is about 1.17%. Even the wage decline of bottom firms is higher, about 0.32%. I also display the same analyses across educational attachments, gender, and race. I find that even for job-stayers individuals, less-educated individuals, black and female workers also exhibits a lower wage growth compared to the benchmark estimation.

2 Literature

This paper is related to the literature that tries to explain the wage outcome in the labor process. Using the method created by Abowd et al. (1999), Card et al. (2013) show how much inequality has increased in Germany after reunification. Song et al. (2019) do the same exercise and provide evidence that the increase in earnings dispersion has also occurred in the United States, highlighting the firm's role in this process. On the other hand, Alvarez et al. (2018) decompose the role of firms and workers effects to see the role of the former in the decrease of inequality that occurred in Brazil from 1996 to 2012, using the same matched employee-employer data that I use in our article, *RAIS*.[3] Arellano-Bover and Saltiel (2022), using *RAIS*, show how different firm classifications impact the learning environment through on-the-job human capital accumulation, and this affects lifetime earnings. Hong (2022), for instance, uses an AKM-type model to see how the interaction between coworkers explains wage variation using data from Italy. In a working paper, Card et al. (2023) want to see how the AKM model may explain the inter-industry wage differential. Departing from the analysis above, where the fixed effects are time invariant, Lachowska et al. (2023) and Engbom et al. (2023) go beyond and see how the AKM model would behave if the fixed effects change according to the period, both finding a small gain of changing from time-variant to time-invariant fixed effects in short intervals period of the sample.[4]

On the theoretical side of the specifics determinants of wage growth, Bagger et al. (2014) extends Postel–Vinay and Robin (2002) and Cahuc et al. (2006) and show how human capital and job search shape wages in the early stages of a career. Ozkan et al. (2023) extends such framework to see how wage growth through different ages affects lifetime earnings inequality. McCrary (2022) constructs a model with decreasing returns to scale on the production side to explain job ladder and earnings dynamics. On an extension of Mincer (1974), Deming (2023) shows how the college premium impacts wage growth through the life cycle and how this is sorted due to different occupations. Also, Albrecht (2022) analyzes earnings losses throughout the life cycle and the role of human capital in that. Our work also dialogues with Sørensen and Vejlin (2011) and extends Gregory (2021) to see how firms affect wage growth after five years of hiring.

As far as I know, I am the first to decompose the role of firms in wage growth in developing countries, using this to predict earnings growth for the next five years. As explained in the first part of the introduction, I run an AKM model decomposing the effects of firms and workers in wage growth using a very rich matched employer-employee dataset for Brazil. Next, I feed the coefficients from my AKM estimations to see earnings growth according to firm's ranking percentile.

[3] Engbom and Moser (2022) go beyond and try to see the role of minimum wage in compressing earnings inequality in Brazil.

[4] Lachowska et al. (2023) highlights that it might be important to correct the mobility bias problem depending on the sample interval. Engbom et al. (2023) argue that time-varying effects become more important as the sample interval increases.

3 Data

This article uses a confidential administrative data set from Brazil: The *Relação Anual de Informações Sociais (RAIS)*, which contains wages and demographic characteristics of workers as reported by the employer. Those linked employer-employee records are constructed from a mandatory survey filled annually by all registered firms in Brazil and administrated by the Ministry of Labor and Employment. Data collection was initiated in 1986, but I have used it since 2009 for the state of São Paulo, the largest of 27 states in Brazil. The data set completely covers all the formal workers and firms in Brazil. The Ministry is levied on incomplete and late reports, and as a result, many businesses hire a specialized accountant to help with the completion of the survey, as described by Alvarez et al. (2018).

The data set contains person, firm and establishment identifiers, which remain fixed period-by-period. With those, is possible to link multiple workers to their employers and follow those over time. The earnings variable is created to allow only labor income or another type of payment strictly related to labor, not relying on other sources of income such as capital income or transfers.

I follow Alvarez et al. (2018) and exclude observations with either firm or worker identifiers reported as invalid and data points with missing wages. Also, I exclude workers reported to work less than 20 hours per week and all public employees. I restrict our attention to workers from age 25-65.[5]

In Table 1, I report key summary statistics for the RAIS data from 2009 to 2015. In Table 2, I provide some firm characteristics related to the firm size.

On average, workers are 38.6 years old and, in your majority, male (58%). Here, I split the sample into only two race categories: black (23%) and white. Regarding their educational characteristics, 33% have an educational level lower than high school, 44% have only a high-school education, and 23% have an educational level above high school, including college. Their tenure spell average is about 5.6 years. The average log monthly wage in 2015 prices is about 7.66, and the wage growth displays a positive result of 3%.[6] I use a large database that constitutes all formal workers from the biggest state in Brazil, São Paulo. Even after removing part-time workers, individuals under twenty-five and more than sixty-five years old, I still have almost 12 million workers in roughly 644 thousand firms, constituting nearly 38 million observations.

[5]This table consider all workers regarding if the workers stays or not on the job.

[6]Here, I aggregate all race categories in white and black. Also, I use the Brazilian Consumer Price Index (*Índice de Preço ao Consumidor Amplo (IPCA)* to adjust the wage variables to 2015 prices, the last year of our sample.

	Mean	St. Dev.	Min	Max
Workers				
Age	38.55	9.33	25	65
Black	0.23	0.42	-	-
Male	0.58	0.49	-	-
Less than high school (LHS)	0.33	0.47	-	-
High school (HS)	0.44	0.50	-	-
Above high school (AHS)	0.23	0.42	-	-
Tenure spell	5.45	4.92	2	56
Monthly log wage (in 2015 prices)	7.66	0.74	5.26	11.70
$\triangle \log w_{ijt}$ (in 2015 prices)	0.03	0.14	-0.65	0.71
Number of observations				
Number of workers	11.853.869	-	-	-
Number of firms	644.075	-	-	-
Total number of observations	37.797.363	-	-	-

Table 1: **RAIS Data Summary**: I include individuals from 25 to 65 years old in this sample from the largest state of Brazil, São Paulo. Workers included have full-time job and work more than 20 hours a week. Means are computed the whole period, from 2009 to 2015.

In Table 2, I can see that most firms (14.3%) report having between 50 to 99 employees. 9.2% of the firms have more than 1000 employees while 2.5% of them have only 1 to 4 employees.[7]

4 Two-way Fixed Effects Model

I will use a two-way fixed effects model based on Abowd et al. (1999). But instead of regressing the wage level on the covariates, I am going to follow the approach of Sørensen and Vejlin (2011) and Gregory (2021) and decompose the wage growth into a linear relationship between observed covariates, individual and firms fixed effects. While most of the papers that rely on the AKM method want to analyze how workers' and firms' premium affects wage levels, I will see firms' role in explaining the wage growth from one period to the other.

Let $i \in \mathcal{I} = \{1, ..., I\}$ index workers. The worker i will be represented by N_i observations indexed by $n \in \mathcal{N}_i = \{1, ..., N_i\}$, totaling $N^* = \sum_{i \in \mathcal{I}} N_i$ observations in the data set. $\mathcal{J} = \{1, ..., J\}$ indicates the set of firms. For worker i, employed at establishment j in

[7]Our *RAIS* database only has information about formal firms. One possible explanation for the small share of firms with 1 to 4 employees is that most are informal. See Ulyssea (2018).

	Share
Firm Size	
1 - 4 employees	2.5%
5 - 9 employees	7.3%
10 - 19 employees	9.9%
20 - 49 employees	12.1%
50 - 99 employees	14.3%
100 - 249 employees	11.0%
250 - 499 employees	11.9%
500 - 999 employees	8.5%
1000 + employees	9.2%

Table 2: **RAIS Data Summary**: Share of firms by size.

year t, wage growth is defined as $\triangle \log w_{ijt} = \log w_{ijt} - \log w_{ijt-1}$. As usual in this type of exercise, I select the most connected set as possible, as shown by Abowd et al. (1999), worker and firm effects can only be separately identified within a connected set of workers and firms that shows variation in the mobility of workers (job-to-job transition). I run the following regression, with log wage growth as the dependent variable:

$$\triangle \log w_{ijt} = \alpha_i + \psi_j + \gamma_t + \boldsymbol{\beta X_{ijt}} + \epsilon_{ijt} \tag{1}$$

As usual in this AKM-type model, I have worker fixed-effect, α_i, firm fixed-effect, ψ_i, a set of year dummies, γ_t, and time-varying covariates, in that case, age and tenure and their respective squared value.[8] I want to see wage growth for those who experience a job-to-job transition and for job-stayers. More precise, opening the vector $\boldsymbol{\beta X_{ijt}}$, I have:

$$\triangle \log w_{ijt} = \alpha_i + \psi_j + \gamma_t + \beta_1(age_{it} - 40)^2 + \beta_2(age_{it} - 40)^3 + \beta_3 tenure_{it} + \beta_4 tenure_{it}^2 + \epsilon_{ijt} \tag{2}$$

Here, I am following Card et al. (2018) and normalizing *age* to deal with the fact that controlling for a set of year indicators γ_t may cause an identification problem with individuals age. I introduce second and third-order polynomials in age and restrict them to

[8] Here, I am considering time-invariant firm fixed effects. For time-variant, see Lachowska et al. (2023) and Engbom et al. (2023).

flat at age 40.[9]

I follow a firm-specific wage profile (wp) as the sum of wage growth depending on firm-fixed effects. I define a as age. Let $j(pth)$ be the firm j at the pth percentile of the ψ_j distributions. I set the worker fixed-effects equal to zero, i.e., $\alpha_i = 0$. The function of years of hire, τ, for a worker at the firm percentile pth with age a is:

$$wp_a^{j(pth)}(\tau) = \sum_{t=1}^{\tau} \triangle \widehat{\log w_{i,j(pth)}^a} \tag{3}$$

where the calculation of the right-hand side is calculated as the following:

$$\widehat{\log w_{i,j(pth)}^a} = \widehat{\psi_{j(pth)}} + \widehat{\beta_1}(a - 40 + \tau)^2 + \widehat{\beta_2}(a - 40 + \tau)^3 + \widehat{\beta_3}\tau + \widehat{\beta_4}\tau^2 \tag{4}$$

Hence, the wage profile is calculated as the cumulative sum of predicted growth in each previous year. Thus, each estimation of the coefficients in Equation 2 is used to feed Equation 4 and then used to calculate the summation in consecutive years, giving the wage growth profile $wp_a^{j(pth)}(\tau)$ for each percentile pth, age a, and years since hire τ, as showed in Equation 3. The coefficients are displayed in Table 3.

[9]Card et al. (2018) show that normalizing for different ages has several wage-level variance implications. For instance, it may change the covariance signal between person effects and time-varying controlling factors, given by the relation between year-fixed effects and tenure.

	All individuals	LHS	HS	AHS	Female	Black
	(1)	(2)	(3)	(4)	(5)	(6)
$(age-40)^2$	0.00009***	0.00009***	0.00009***	0.00018***	0.00009***	0.00010***
	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
$(age-40)^3$	0.00000***	0.00000***	0.00000***	-0.00001***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
tenure	0.00483***	0.00302***	0.00513***	0.00740***	0.00545***	0.00393***
	(0.00025)	(0.00015)	(0.00020)	(0.00033)	(0.00039)	(0.00033)
$tenure^2$	-0.00010***	-0.00006***	-0.00015***	-0.00012**	-0.00010	-0.00007
	(0.00004)	(0.00001)	(0.00001)	(0.00006)	(0.00006)	(0.00004)
R^2	0.41059	0.49585	0.47917	0.40978	0.43012	0.53117
Adjusted R^2	0.13159	0.19813	0.15487	0.13001	0.13658	0.19461
Observations	39,991,488	11,520,251	16,670,425	8,392,840	16,333,758	8,179,941
Year fixed effects	✓	✓	✓	✓	✓	✓
Person fixed effects	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓

Table 3: **AKM model for job-changers and job-stayers**: Columns 2, 3, and 4 show specifications in which the reduced form exercise is measured for individuals with less than high school (LHS), high school (HS), and above high school (AHS), respectively. All specifications include a constant, not reported. Standard errors are presented in parenthesis, * indicates significant at the 90 percent confidence level and ** a 95 percent confidence level and *** a 99 percent confidence level. *Source*: RAIS

5 Results

This section presents the results for the Equation 4. The model is estimated in terms of wage growth as in Equation 3, and I feed firms fixed effects as well coefficients in age and tenure in Equation 4 and predict the wage profiles for different ages, levels of education, gender and race. Here, I am considering individuals who stayed on the same job or experienced a job-to-job transition from one period to the other.

Inspecting Figure 1, I can see very different results among firms percentiles. The wage growth for workers that are twenty-five years old and have a job in firms that belong to the 90th percentile may experience an accumulated earnings growth of 1.34% (blue long-dashed line) after five years. For individuals working in the 75th percentile firms, the sum of predictive earnings equals 0.90% (green dot-dashed line); for individuals in the 50th percentile, the sum of predictive earnings is 0.53%. The results of the 25th percentile show a 0.16% earnings growth (brown solid line), which indicates that for that percentile, wage growth starts to become flatter and, for the last percentile analyzed (10th), I have a wage decline of 0.33% (yellow dashed line), i.e., for individuals that work in the bottom firms percentile, after five years, they experience a wage decline if the earnings growth growth only depend on firms characteristics, age and tenure.

When workers are older (thirty years), the sum of predictive earnings becomes flatter compared to younger individuals.[10] At the 90th percentile, accumulated earnings grow 1.28% while at 75th percentile, the growth is estimated in 0.83%. Workers in the 50th percentile experience an earnings growth of 0.47%. In the last percentiles analyzed, individuals showed an earnings decline of 0.40%. The same pattern occurs in individuals when they are thirty-five years old. While individuals in the most productive firms show a sum of predictive earnings of 1.25%, the workers in the 10th percentile show a wage decline of 0.42%.

5.1 Sum of predictive earnings by education

Now, I will explore the same sum of predictive earnings but segmented by education. This exercise allows a better comparison with the results of Gregory (2021). I start with the results of individuals twenty-five years old with less than high school (LHS) education, as displayed in Figure 2. Workers of that group show that, after five years of hiring, they accumulated 1.10% earnings growth for those firms in the 90th percentile. For those that have a job in firms in the set of 75th percentile, they displayed an earnings growth of 0.53%. For individuals in the 50th percentile, there is an earnings growth of 0.06%. Unlike the general case, for those individuals with lower education, their earnings growth starts to decline even though workers are in 25th firms, displaying a wage decline of 0.39%. For firms in 10th percentile, the wage decline is of 0.99%. For comparison, Gregory (2021) shows that for vocational workers, for firms in the 90th percentile, the sum of predictive earnings is almost 0.25%, while for those in the 10th percentile, the decline is less than 0.1%.

The same flat pattern occurs when workers are older and individuals are less-educated. First, I analyze the wage growth path for workers with less than high school degree (LHS). Individuals at the top firm percentile accumulate a 1.03% earnings growth while those at

[10] See Albrecht (2022).

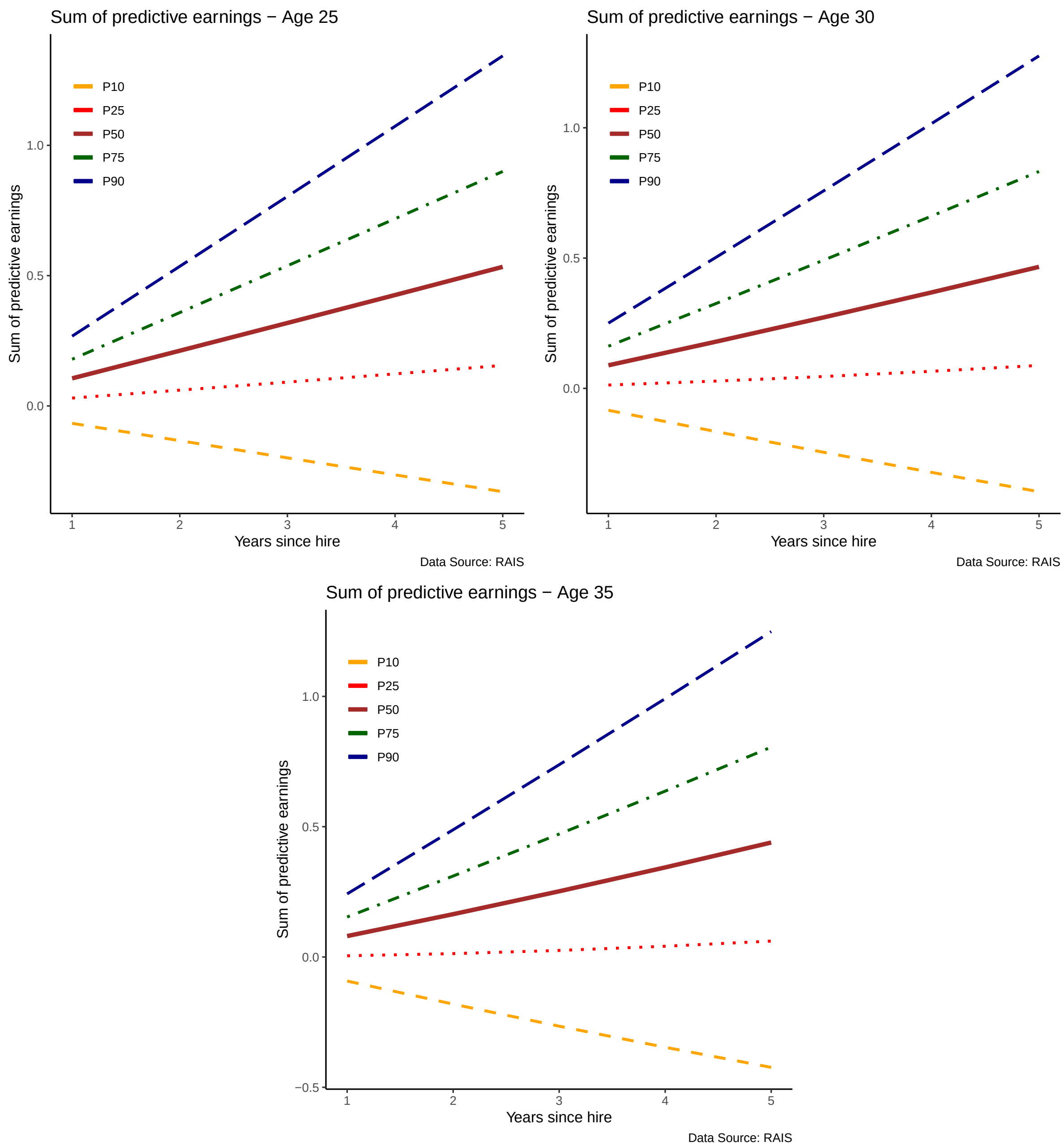

Figure 1: **Firms-specific earnings growth profile for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

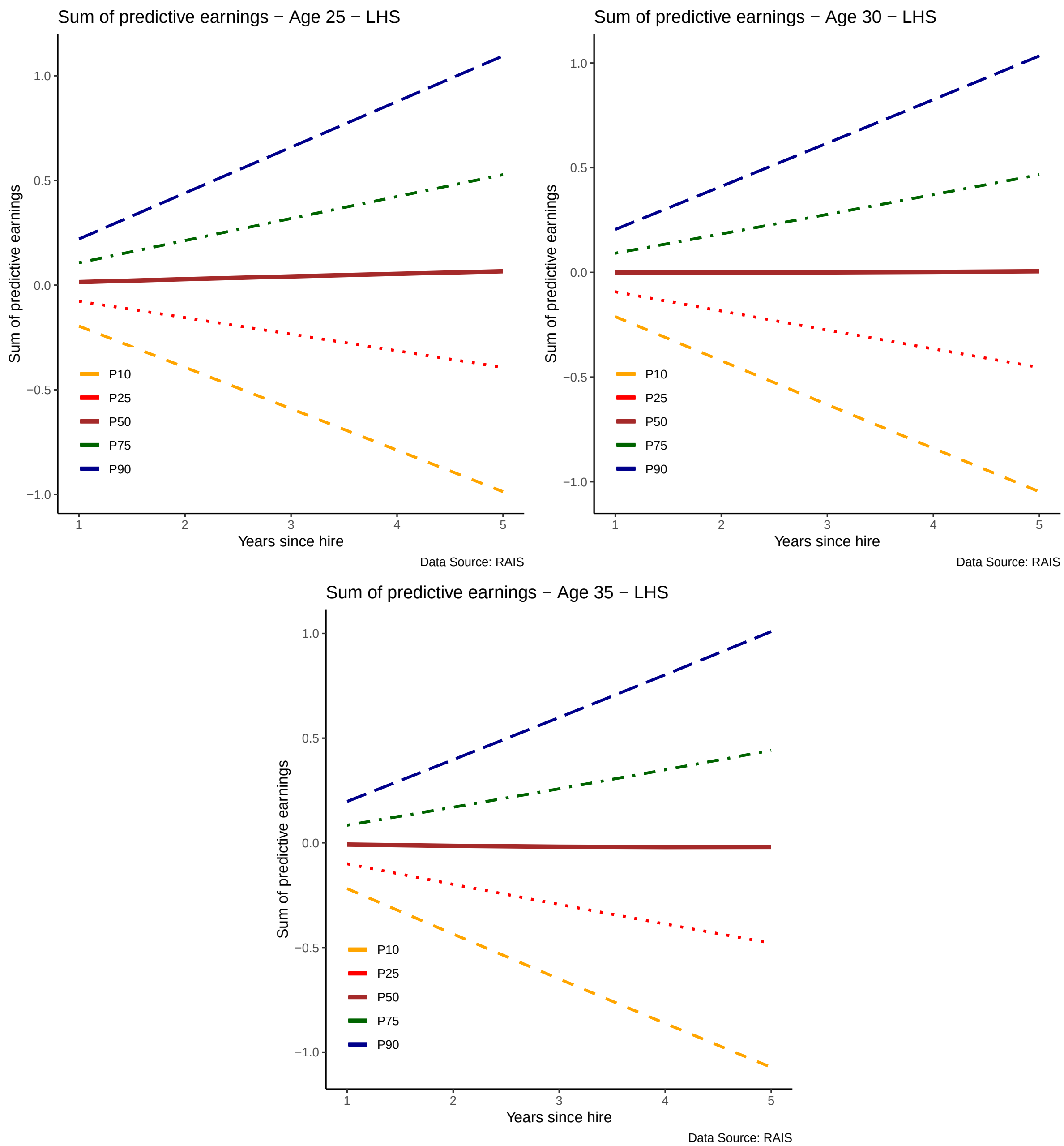

Figure 2: **Firms-specific earnings growth profile for less than high-school for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

the bottom experience a wage decline of 1.07% when individuals are thirty years old. For older workers, the top percentile displays an earnings growth of 1.01% while the bottom shows a wage decline of 0.20%.

On the other hand, individuals that have at least high school (HS) show better results than less educated workers, as displayed in the Figure 3. Twenty-five years old individuals at the top percentile have an earnings growth of 1.60%, while those at the bottom display a decline of 0.52%. When individuals get more senior (thirty years), the same flat pattern appeared, with individuals at the top percentile with earnings of 1.54% while those at the bottom experienced a decline of 0.59%. For those 35 years old individuals, I have an increase of 1.51% for the top and a drop of 0.61%, respectively.

I now inspect the sum of predicting earnings of individuals with an educational level above high school (AHS), which consists of individuals with some college or completed college degree. The graph is displayed in Figure 4. For twenty-five years old workers in the top firms percentile, the sum of predictive earnings is equal to 1.14% while individuals in the bottom percentile show an earnings decline of 1.10%. The same flat pattern occurs when they get older. Thirty years old individuals show a 1.01% earnings growth for top firms while they lose almost 1.23% if they are employed at firms at the bottom of firms' fixed-effects distribution. For thirty years individuals, the sum of predictive earnings achieves 0.96% after 5 years, while individuals in the bottom, after five years, suffer an earnings loss of 1.28%.

5.2 Sum of predictive earnings by gender and race

Now, I do the same exercise but to see the sum of predictive earnings growth only for women and for black workers. I exhibit the results on Figure 5 and Figure 6. I find that, for younger woman working in the top firms, after five years, their earnings growth will be of 0.86% while for the bottom firms, the wage decline will be of 0.98%. Hence, women experience a slow wage growth when compared to the full sample. When they are older, as the pattern already explained before, the wage growth starts to become flatter. Workers on the 90th firms percentile experience an earnings growth of 0.79% while in the bottom, the 10th percentile, has an earnings decline of 1.04%. For woman with thirty-five years old, the earnings growth in the top percentile is about 0.77% while the wage decline for workers in the bottom firm is about -1.07%.

For young black workers from the top firms experience an earnings growth of 0.87% while in the bottom firms, on the other hand, they have an earnings loss of 1.49%. Hence,

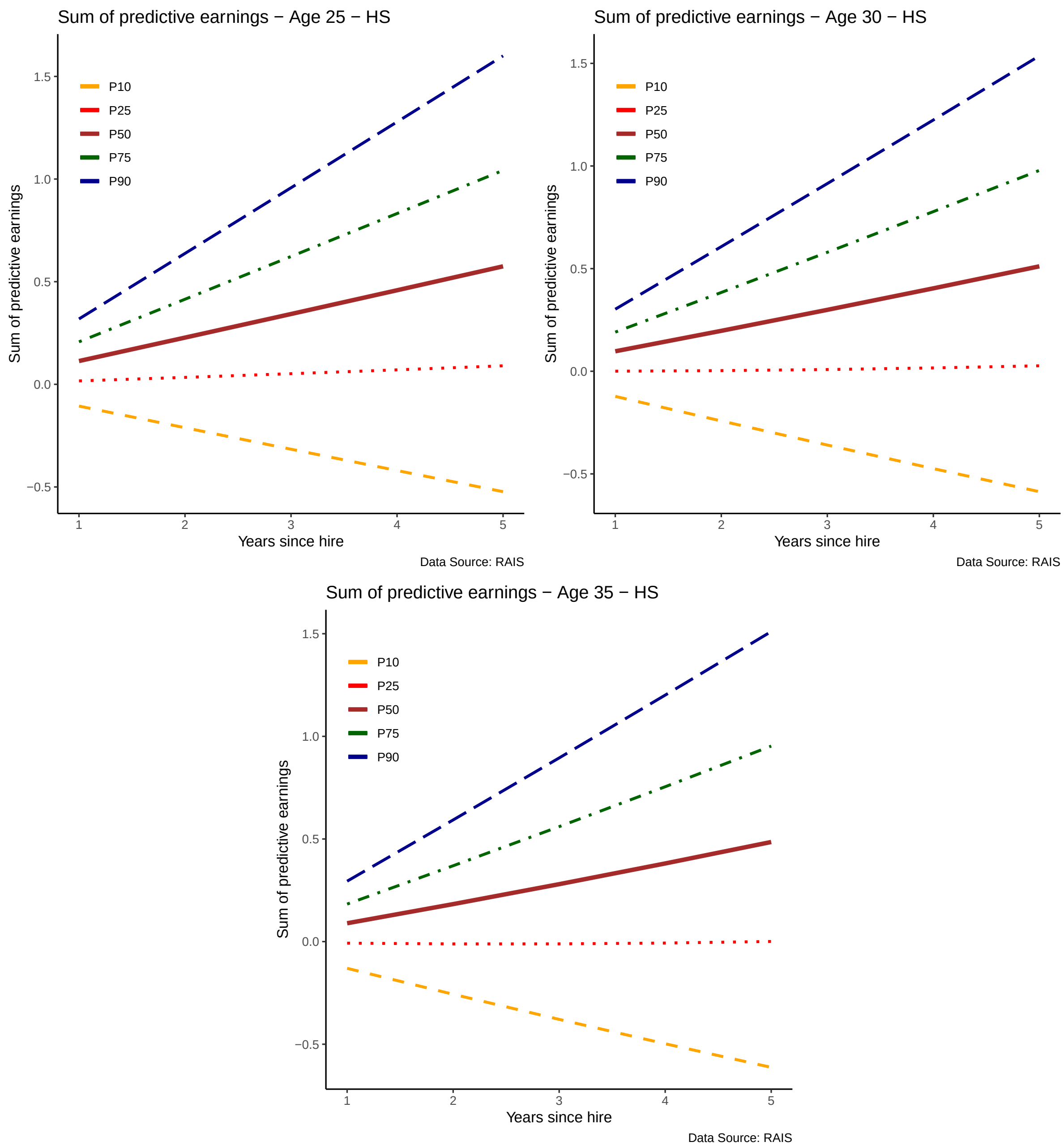

Figure 3: **Firms-specific earnings growth profile for high-school for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

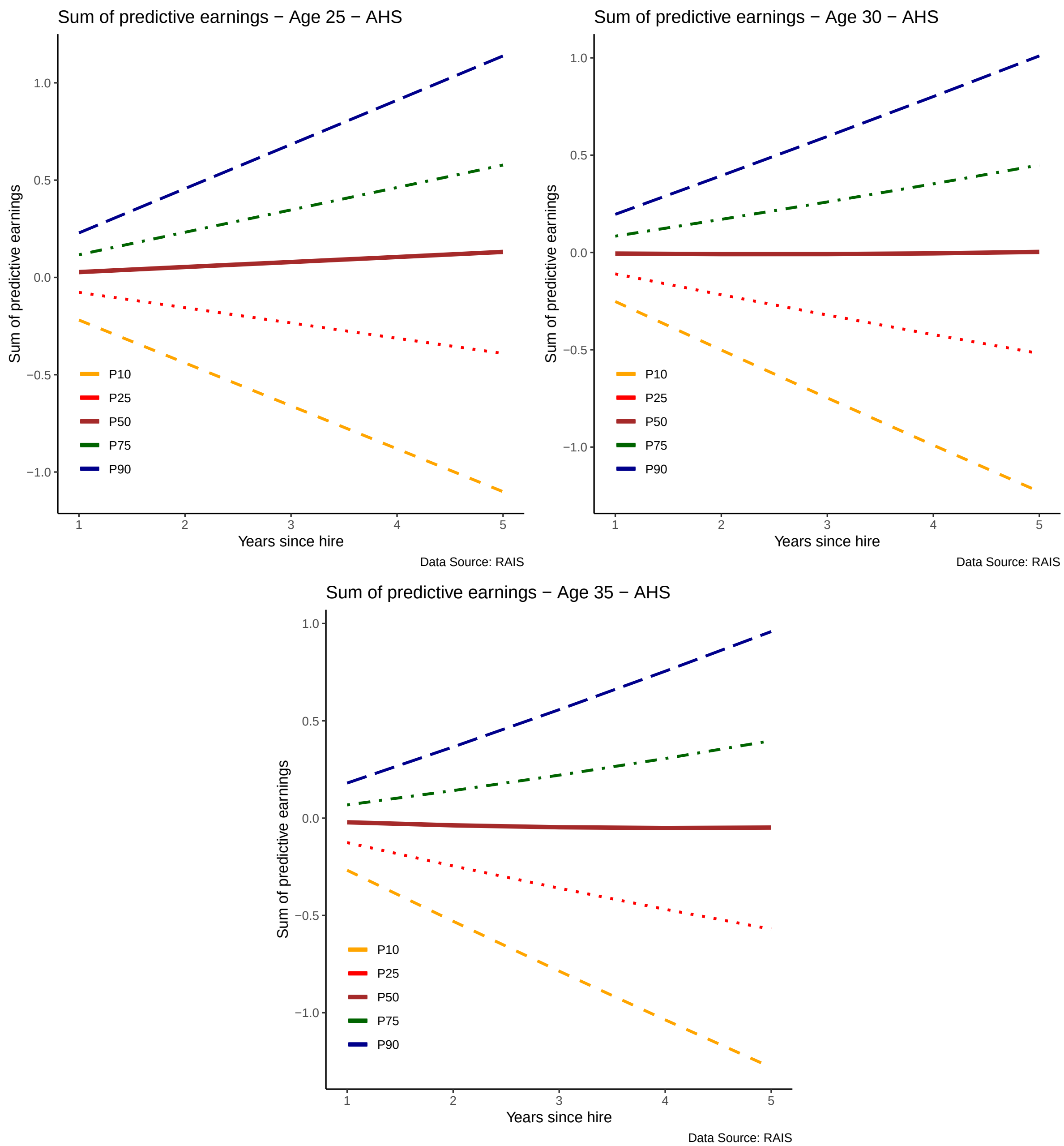

Figure 4: **Firms-specific earnings growth profile for above than high-school for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

the wage decline for black workers in the bottom firms is, in absolute value, greater than in any other comparison I did in the previous paragraph. For thirty years black workers, the wage growth for top firms is about 0.80% while the decline for workers in bottom firms is 1.55%. Again, the flat pattern appears when I consider the wage growth for thirty-five years individuals. The wage growth for black workers in top firms is about 0.78%, and for bottom firms, the wage decline is about 1.58%.

Therefore, young and black women has a lower wage growth than the full sample, and when I analyze the role of bottom firms, their wage decline is even larger in absolute value than the full sample estimation.

6 Results for only job-stayers

This section presents the results for the Equation 4 but only for job-stayers. Again, the model is estimated in terms of wage growth as in Equation 3, and I feed firms fixed effects as well coefficients in age and tenure in Equation 4 and predict the wage profiles for different ages, levels of education, gender and race. The coefficients are displayed in Table 4.

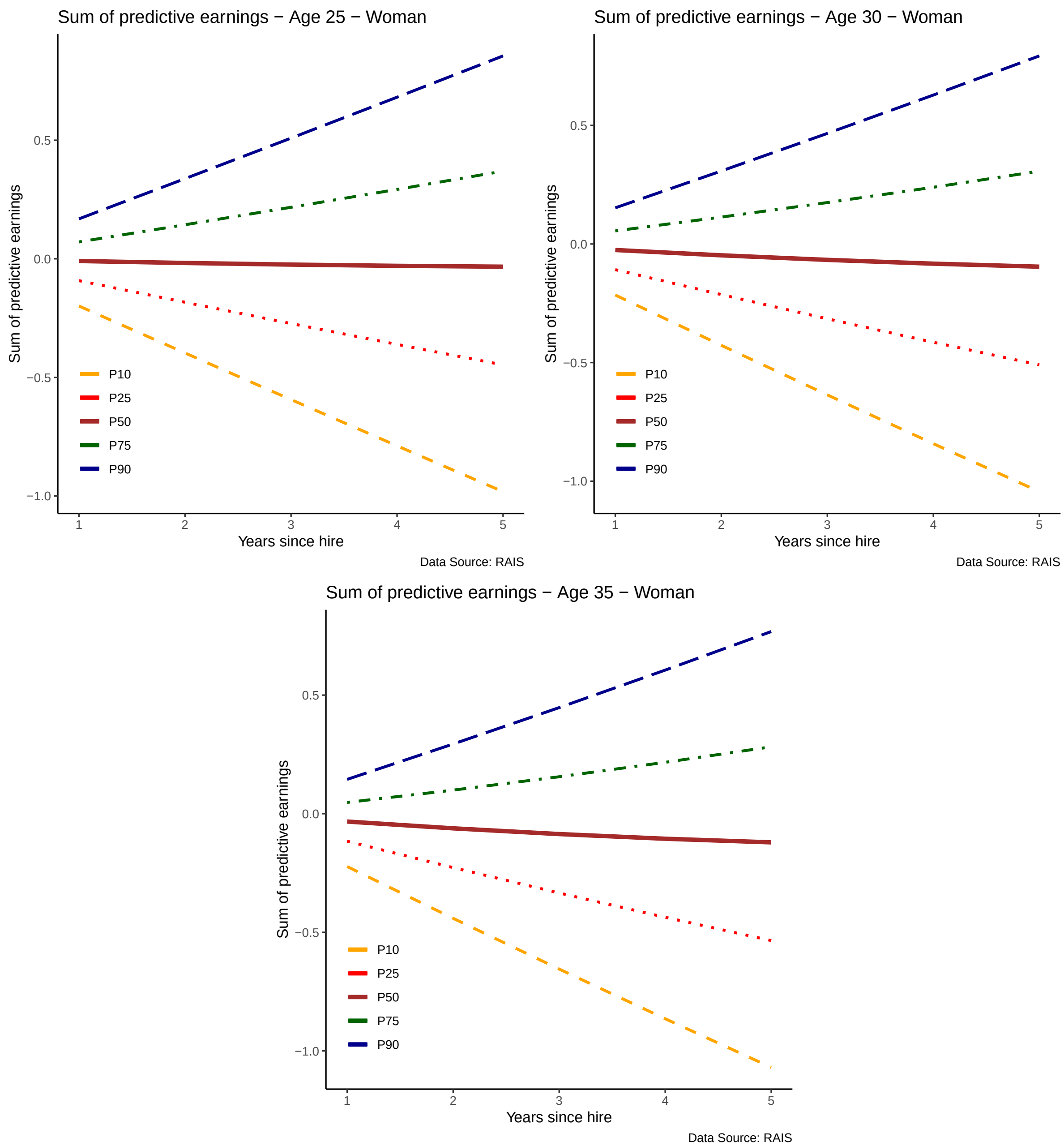

Figure 5: **Firms-specific earnings growth profile for female workers for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

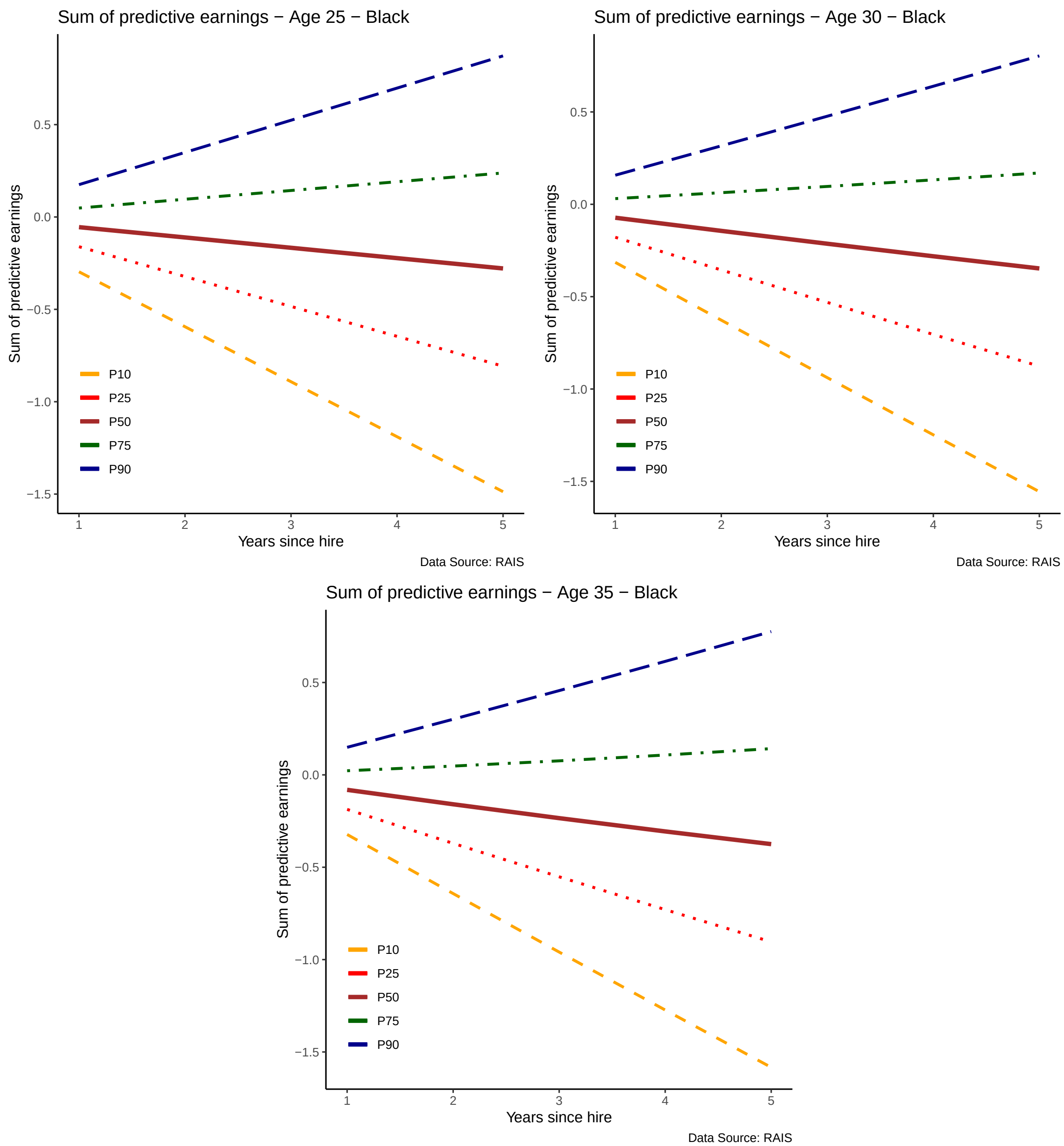

Figure 6: **Firms-specific earnings growth profile for black workers for job-changers and job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

	All individuals	LHS	HS	AHS	Female	Black
	(1)	(2)	(3)	(4)	(5)	(6)
$(age-40)^2$	0.00008***	0.00009***	0.00009***	0.00015***	0.00008***	0.00009***
	(0.00001)	(0.00000)	(0.00000)	(0.00002)	(0.00001)	(0.00001)
$(age-40)^3$	0.00000***	0.00000***	0.00000***	-0.00001***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
$tenure$	-0.00128***	-0.00139***	-0.00218***	0.00112***	-0.00070**	-0.00247***
	(0.00021)	(0.00016)	(0.00020)	(0.00037)	(0.00035)	(0.00030)
$tenure^2$	0.00010***	0.00009***	0.00011***	0.00008	0.00011*	0.00016***
	(0.00004)	(0.00001)	(0.00001)	(0.00006)	(0.00006)	(0.00004)
R^2	0.43550	0.50206	0.49491	0.42505	0.45192	0.53729
Adjusted R^2	0.15663	0.20333	0.17043	0.14447	0.15857	0.20021
Observations	37,797,363	10,780,897	15,423,191	7,899,926	15,385,360	7,518,478
Year fixed effects	✓	✓	✓	✓	✓	✓
Person fixed effects	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓

Table 4: **AKM model for only job-stayers**: Columns 2, 3, and 4 show specifications in which the reduced form exercise is measured for individuals with less than high school (LHS), high school (HS), and above high school (AHS), respectively. All specifications include a constant, not reported. Standard errors are presented in parenthesis, * indicates significant at the 90 percent confidence level and ** a 95 percent confidence level and *** a 99 percent confidence level. *Source*: RAIS

Inspecting Figure 7, I can see very different results among firms percentiles. The wage growth for workers that are twenty-five years old and have a job in firms that belong to the 90th percentile may experience an accumulated earnings growth of 1.17% (blue long-dashed line) after five years. For individuals working in the 75th percentile firms, the sum of predictive earnings after five years is equal to 0.77% (green dot-dashed line); for individuals in the 50th percentile, the sum of predictive earnings is 0.44%. The results of the 25th percentile show a 0.1% earnings growth (brown solid line), which indicates that for that percentile, wage growth starts to become flatter and, for the last percentile analyzed (10th), I have a wage decline of 0.32% (yellow dashed line), i.e., for individuals that work in the bottom firms percentile, after 5 years, they experience a wage decline if wage growth only depend of firms characteristics.

When workers are older (30 years), the sum of predictive earnings becomes flatter compared to younger individuals.[11] At the 90th percentile, accumulated earnings grow 1.11% while at 75th percentile, the growth is estimated in 0.71%. Workers in the 50th percentile experience a earnings growth of 0.38%. In the last percentiles analyzed, individuals showed an earnings growth of 0.04%, while the last percentile analyzed resulted in a wage decline of 0.38%. The same pattern occurs in individuals when they are 35 years old. While individuals in the most productive firms show a sum of predictive earnings of 1.09%, the workers in the 10th percentile show a wage decline of 0.40%.

The results described above contrast with those displayed by Gregory (2021). Her sum of predictive earnings growth displays a concave pattern in the function of years hired. Since she shows results depending on educational level, I will do the same, as displayed in the following three figures.

6.1 Sum of predictive earnings by education

Now, I will explore the same sum of predictive earnings but segmented by education. This exercise allows a better comparison with the results of Gregory (2021). I start with the results of individuals 25 years old with an education level Lower than High School (LHS), as displayed in Figure 8. Workers of that group show that, after 5 years of hiring, they accumulated 0.84% earnings growth for those firms in the 90th percentile. For those that have a job in firms in the set of 75th percentile, they displayed an earnings growth of 0.33%. Unlike the general case, for those individuals with lower education, their earnings growth starts to decline even though workers are in 50th firms. After 5 years, they display a wage decline of 0.07%. For firms in 25th percentile, the wage decline is of 0.49%, while almost 0.79% for firms in the 10th percentile. For comparison, Gregory (2021) shows that for vocational workers, for firms in the 90th percentile, the sum of predictive earnings is almost 0.25%, while for those in the 10th percentile, the decline is less than 0.1%. Hence, Brazilian workers have a large standard deviation of earnings growth compared to Danish workers.

The same flat pattern occurs when workers are older and individuals with lower than high school education (LHS). Individuals at the top firm percentile accumulate a 0.78% earnings growth while those at the bottom experience a wage decline of 1.06% when individuals are thirty years old. For thirty-five year old workers, the top percentile displays an earnings growth of 0.75% while the bottom shows a wage decline of 1.09%.

[11]See Albrecht (2022).

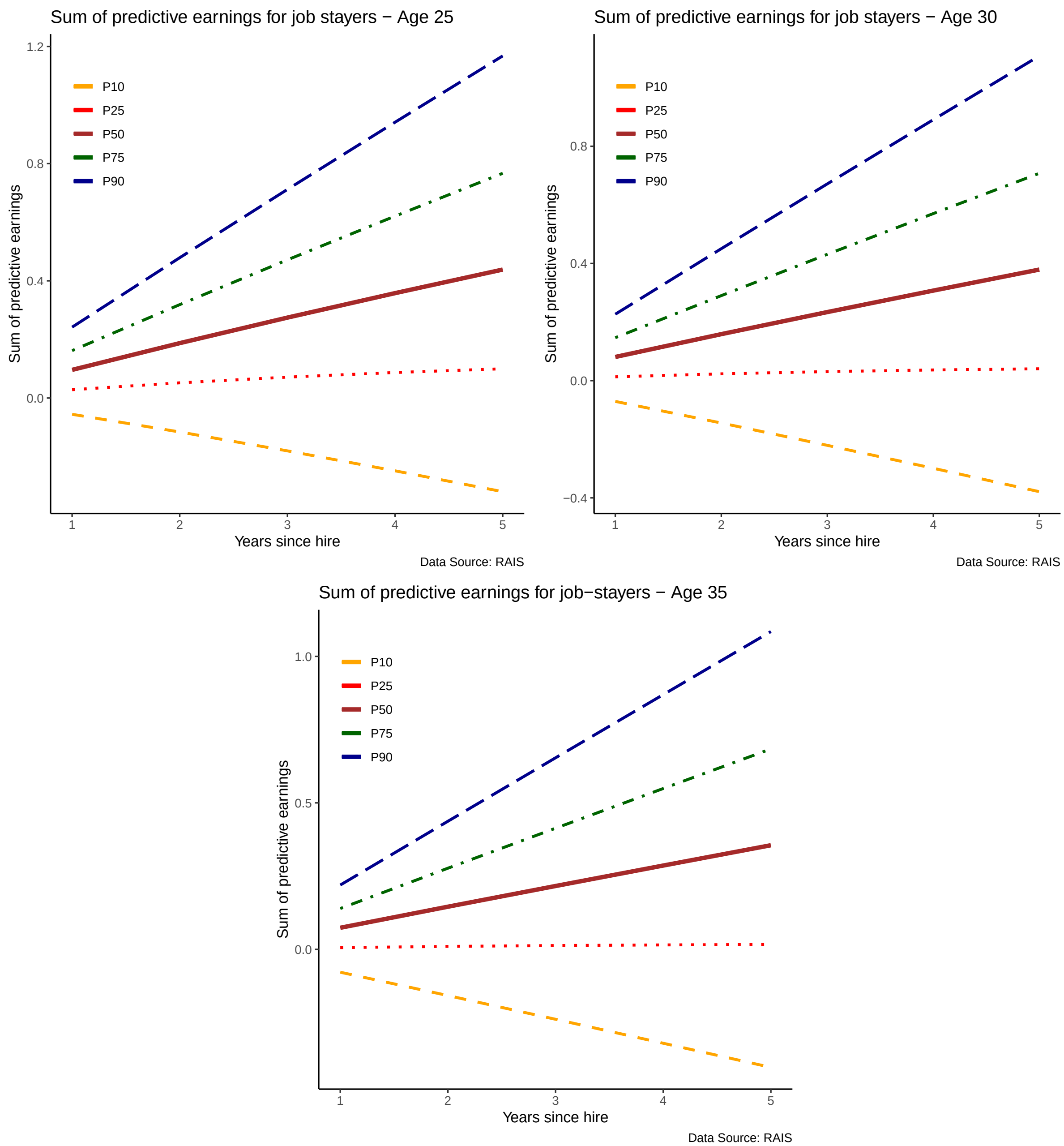

Figure 7: **Firms-specific earnings growth profile for job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

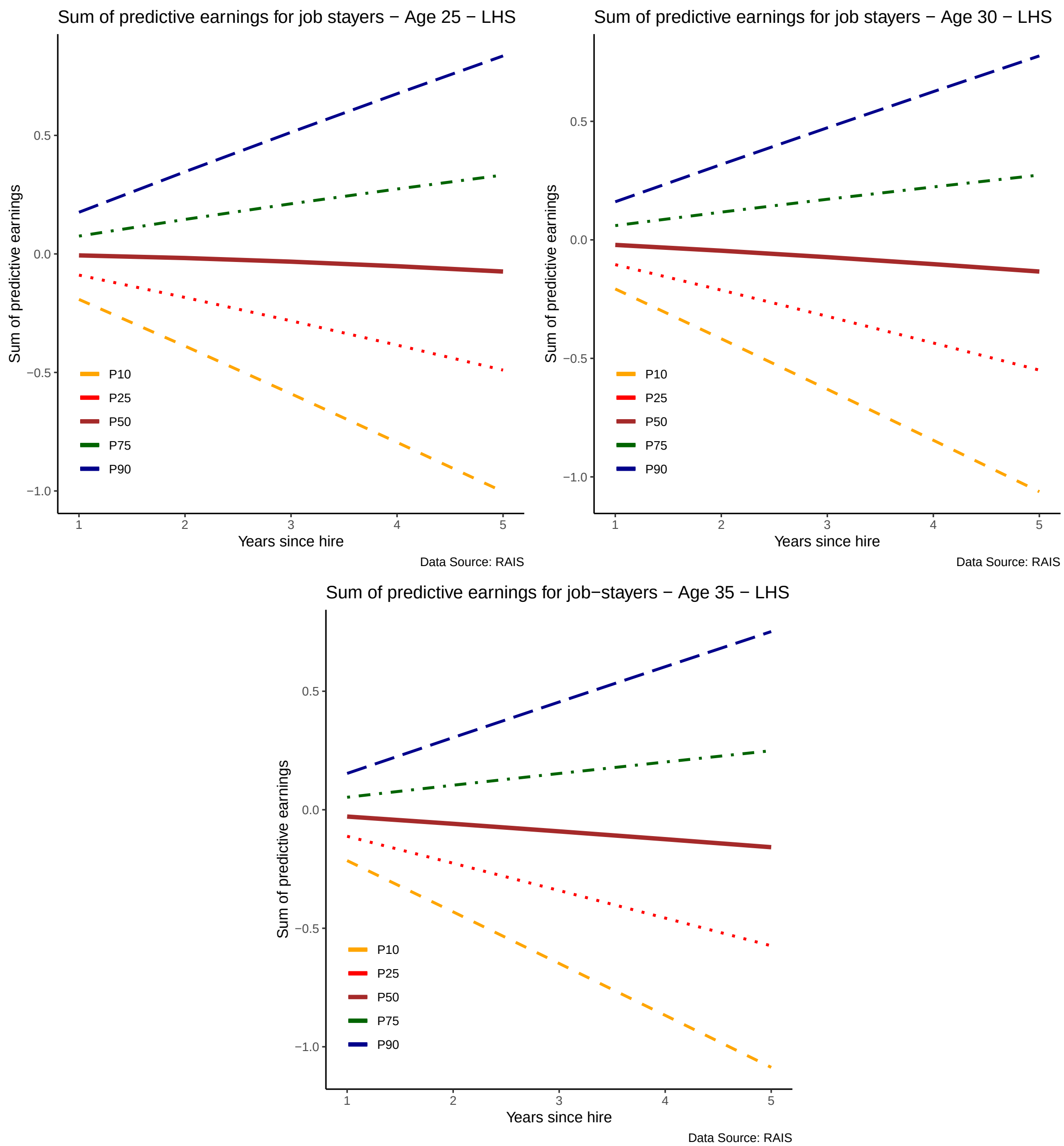

Figure 8: **Firms-specific earnings growth profile for less than high-school for job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

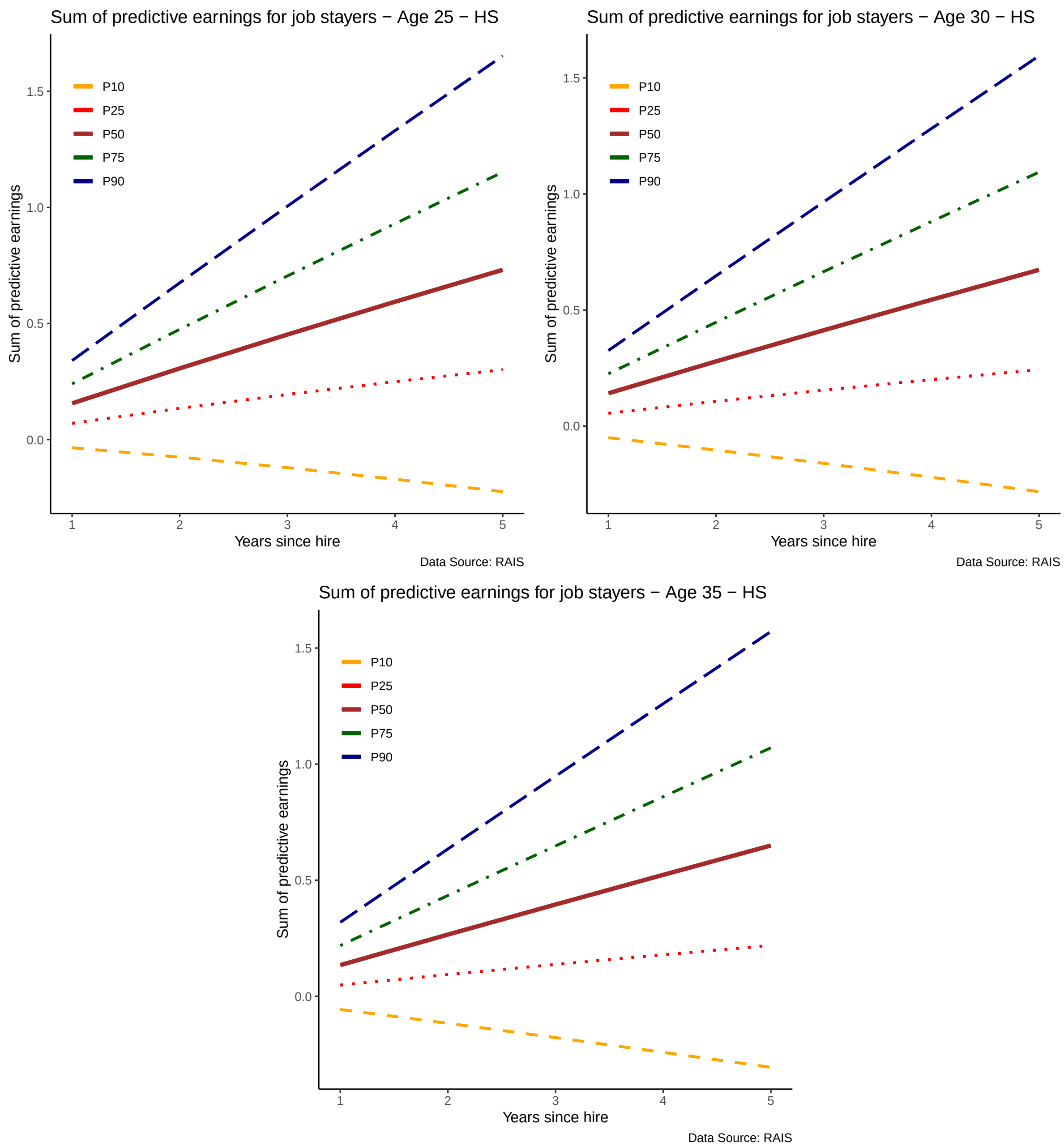

Figure 9: **Firms-specific earnings growth profile for high-school for job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

On the other hand, individuals that have at least high school (HS) show better results than lower educated workers, as displayed in the Figure 9. Twenty-five years old, individuals at the top percentile have an earnings growth of 1.65%, while those at the bottom display a decline of 0.22%. When individuals got more senior (thirty years), the same flat pattern appeared, with individuals at the top percentile earning 1.59% while those at the bottom experienced a decline of 0.28%. For those thirty years old individuals, I have an increase of 1.57% and a drop of 0.31%, respectively.

I now inspect the sum of predicting earnings of individuals with an educational level above high school, which consists of individuals with some college or college degree. The graph is displayed in Figure 10. Interestingly, and in a different direction that Gregory (2021) points out, the earnings growth of those individuals is lower compared to individuals with only high-school degrees. For twenty-five years old workers in the top firms percentile, the sum of predictive earnings is equal to 1.00% while individuals in the bottom percentile show an earnings growth of 0.21%. The same flat pattern occurs when they get older. Thirty-years years old, individuals show a 0.89% earnings growth for top firms while they lose almost 1.00% if they are employed at firms at the bottom of firms' fixed-effects distribution. For thirty-five years individuals, the sum of predictive earnings achieves 0.84% after five years, while individuals in the bottom suffer an earnings loss of 1.04%.

6.2 Sum of predictive earnings by gender and race

In this subsection, I also decompose the wage growth by gender and race, as I did in subsection 5.2. The result for female and black workers are very similar to the situation where job-to-job transition is allowed. The results are showed in Figure 11 and Figure 12.

The wage growth for young female workers in the top firms is about 0.80% while in the bottom firms, in the 10th percentile, is about -0.83%. The same age flat pattern occurs when individuals get older. For thirty and thirty-five years years old, the sum of predictive earnings after five years is about 0.74% and 0.72% in the 90th percentile, while the wage decline in the bottom firms is about 0.88% and 0.90%, respectively.

Again, I document a lower wage growth to black workers when compared to all other individuals, for only job-stayers. The sum of predictive earnings growth for black individuals in top firms is 0.87%. However, in the bottom firms, black workers experience a wage decline of 1.49%. For older workers, the wage growth starts, again, to become flatter. The wage growth is about 0.80% for thirty years old black workers while the wage growth

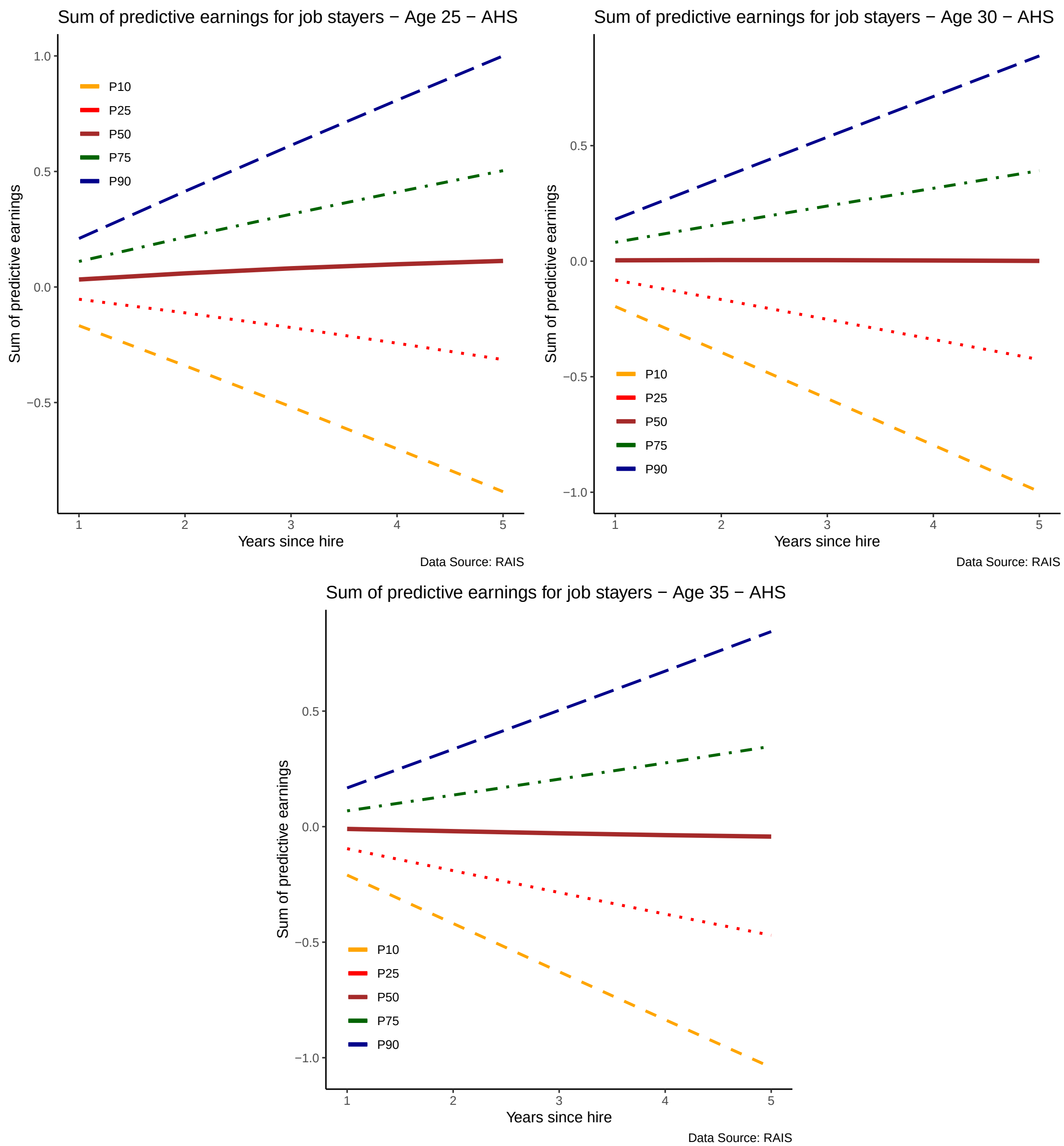

Figure 10: **Firms-specific earnings growth profile for above than high-school for job-stayers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

decline is 1.56%. For thirty-five years old individuals, the wage growth is about 0.80% while the wage decline is 1.58%.

7 Concluding remarks

In this paper, I decompose wage growth in person and firm fixed effects using an AKM model and use the firm's fixed effects to see their role in explaining wage growth. I find that, in general, wage growth is higher for workers who may experience job-to-job transitions compared to only job-stayers. I also document a flat pattern when individuals get older, indicating that wage growth is lower for older individuals.

When I segment my results by level of education, I find that individuals with at least a high school education (HS) have higher earnings than those less than high school, however, HS individuals experience higher earnings than individuals with college and some college degree (AHS). The same pattern occurs only in job-staying individuals.

I also analyzed the results for black and female workers and found that the abovementioned pattern applies to those groups. Moreover, I also document that black and female workers have lower earnings than the general groups analyzed. When I see the impact of bottom firms on those two groups, I see an even larger decline in wage trajectory compared to the full sample.

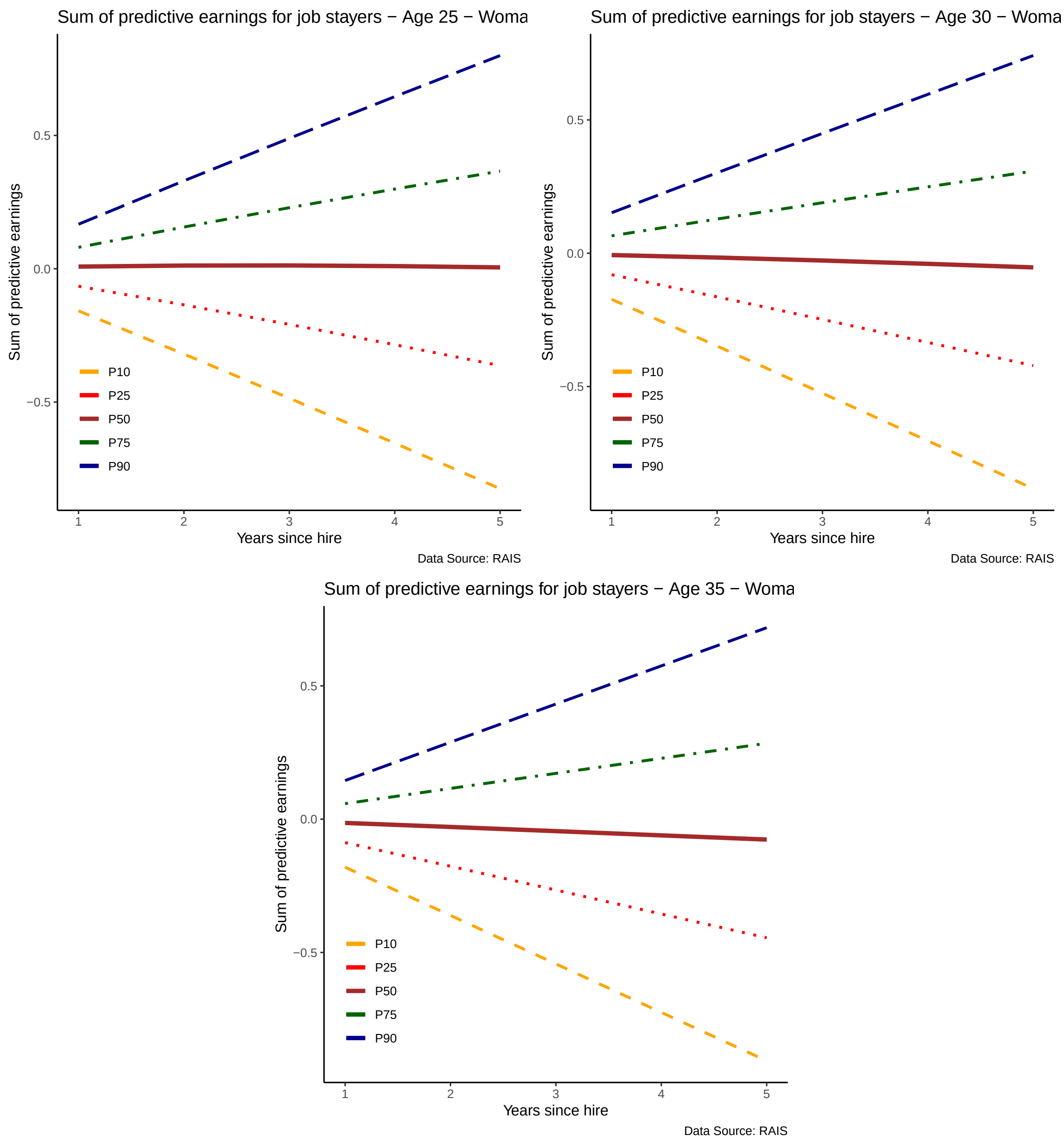

Figure 11: **Firms-specific earnings growth profile for job-stayers and female workers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

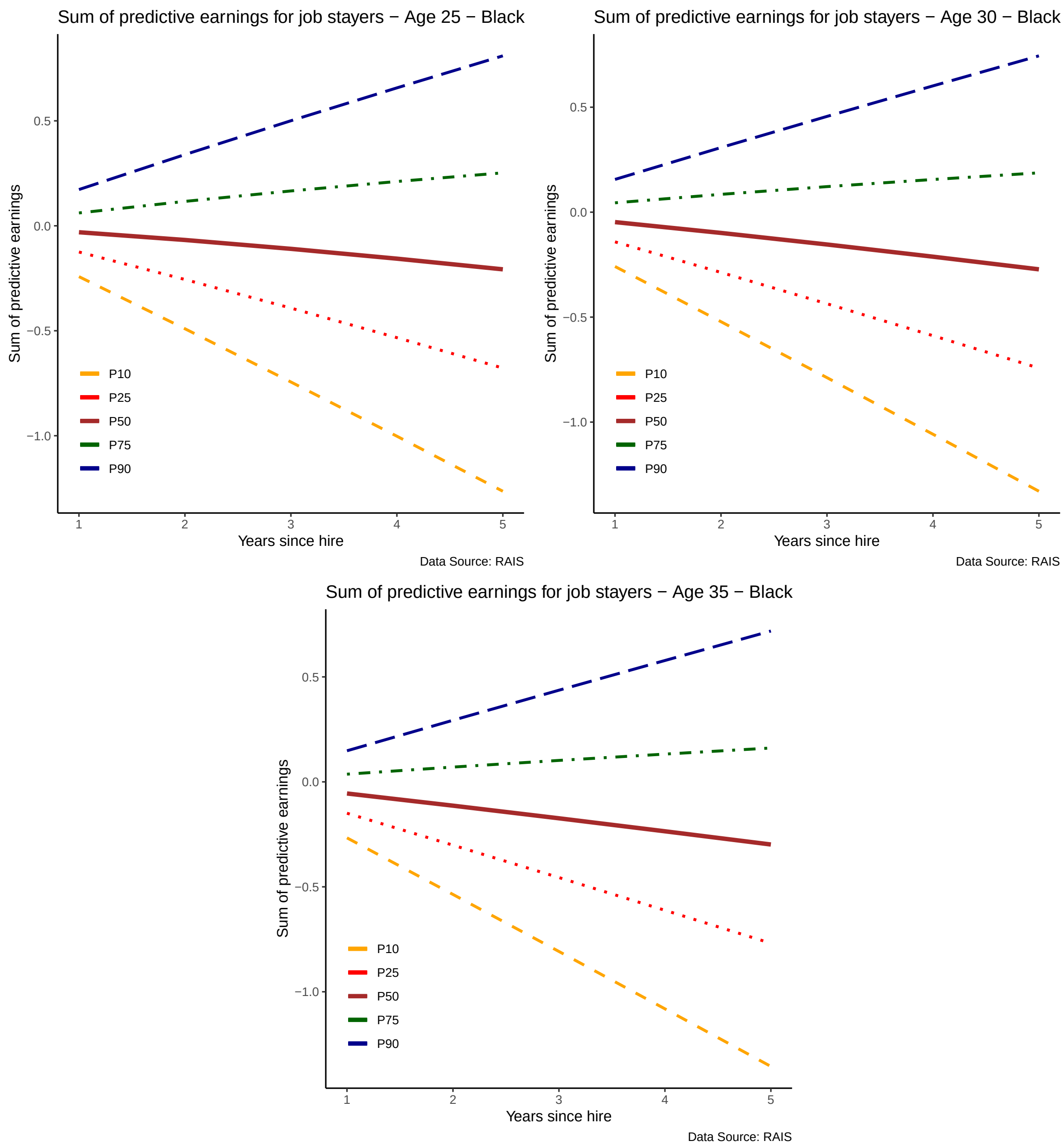

Figure 12: **Firms-specific earnings growth profile for job-stayers and black workers**: Each graph provides the cumulative wages growth estimated from Equation 2. I normalize the individual fixed-effect α_i to be equal to 0. Each series from bottom to the top corresponds to wage growth profile of firms at the percentile *pth* 10, 25, 50, 75 and 90, for different ages.

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