Heterogeneous impacts of domestic outsourcing on wages

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Abstract: This paper assesses the consequences of domestic outsourcing on different groups of workers, stemming from a theoretical model with heterogeneous individuals and firms. We find the wage gap between outsourced workers and non-outsourced ones to be larger for more productive workers, as well as for those who work at sectors where observation of their effort is harder. Furthermore, using Brazilian micro-data and quantile regressions, we demonstrate that the effect of outsourcing on wages grows with income, as suggested by the theoretical model.

Key words: outsourcing, efficiency wage, quantile regression.
JEL classifications: J31, C21.

Resumo: Este artigo avalia as consequências da terceirização doméstica sobre diferentes grupos de trabalhadores a partir de um modelo teórico com indivíduos e firmas heterogêneos. Nossa análise teórica indica que o *gap* salarial para trabalhadores terceirizados deve ser maior para os trabalhadores mais produtivos, assim como para aqueles indivíduos que trabalham em setores em que é mais difícil observar o seu esforço. Além disso, usando microdados brasileiros, nós evidenciamos por meio de um arcabouço de regressão quantílica que os efeitos da terceirização sobre os salários tornam-se mais relevantes para os indivíduos com maior salário, o que corrobora as conclusões do nosso modelo teórico.

Palavras-Chave: terceirização, salário eficiência, regressão quantílica.
Classificação JEL: J31, C21.

Área de submissão: Economia do trabalho

1. Introduction

Over the last two decades, the economic impacts of service outsourcing have generated ever-increasing academic interest (MANKIW and SWAGEL, 2006). Amid these studies (carefully reviewed in the next section), some seek to estimate outsourcing's effects on wages, and overall conclude that outsourced workers earn less than their non-outsourced counterparts.

Williamson (2008) suggests the outsourcing processes can be adopted under very distinct circumstances and with equally distinguished objectives. Thus, workers from different sectors and levels of human capital could be outsourced.

In this paper, we focus on domestic outsourcing – witch contrasts with offshoring (GOLDSHIMIDT and SCHMIEDER, 2017). We evaluate whether the effects of outsourcing on workers' wages are homogeneous or not. We therefore intend to build a highly stylized model that underlines how disparities in the labor outsourcing sector and in the outsourced workers' productivity can influence the observed wage gap.

Moreover, an empirical analysis will be carried in order to test the conclusions of this theoretical model. Data from the Annual Social Information Report (RAIS) for 2014 will be used, and so will a methodology of quantile regression, to explore heterogeneous effects of outsourcing on wages.

This article consists of five sections, in addition to this introduction. Section 2 reviews literature concerning outsourcing in relation to wages. Section 3 develops the theoretical model. Section 4 discusses the database employed, as well as presents the empirical model and its results. Section 5 tests the adjustment of the model when we control for selection of outsourced workers.

2. The impact of outsourcing on wages

As pointed out in the introduction, this paper focuses on domestic outsourcing processes and their implications on the wages of the workers who have been outsourced. Berlinski (2008) is the first paper with similar purpose. He assess the consequences of outsourcing for low human capital workers in the United Kingdom.

The author builds a database for workers from 1995 to 2001 and conducts estimates of a Mincerian equation, which includes a dummy variable for outsourced workers, through Generalized Least Squares (GLS) and propensity score matching, and concludes that the evaluated workers are paid 17% to 19% less than non-outsourced similar employees. His outsourcing definition is somewhat limited, since his database has fewer than sixty outsourced workers.

Dube and Kaplan (2010) also perform an empirical work to analyze the effect of outsourcing on low-human capital workers, more specifically guards and janitors, in the U.S. An outsourcing indicating variable, similar to the one used in this study, is created by the combination of information on the job performed by each worker and the sector in which they work, using micro-data from the Current Population Survey (CPS), between 1983 and 2000.

The authors construct a Mincerian equation and estimate it via the Generalized Least Squares (GLS) method. In this first estimation, it is shown that outsourced janitors make about 5% less, while guards earn about 20% less, when compared to non-outsourced workers in the same occupation.

Dube and Kaplan (2010) then examine if unobservable differences in productivity may explain the wage gap. They build a two-period panel and individuals with the same occupation are observed on each of the periods. Subsequently, a new wage equation is estimated through the first difference method. The outsourcing wage penalties still remain though, around 7% for janitors and 12% for guards. This methodology was, then, used in all subsequent papers on the topic.

Thereby, the authors find outsourced workers are paid less due to their contract type. They also conclude that the penalty suffered by the workers is not explained by low rent pass-through or compensating differentials, so it must be associated with some non-taken rent, like the one obtained through unionization, for instance; since the persistent estimated difference is not compatible with the hypothesis of a competitive market. Despite these considerations, Dube and Kaplan (2010) do not go further in the outsourcing wage penalty theory.

Stein, Zylberstajn e Zylberstajn (2016) apply the previous methodology to Brazilian data. The authors consider outsourced workers in the cleaning, security, technology of information (TI), maintenance and research and development (R&D). The author show that almost all the raw outsourced wage gap in their sample can be explained by different individual characteristics. Once they control for variant observable and fixed unobservable characteristics through the first-difference method, they conclude that the average wage gap is about only 3%.

They do not systematically analyze how the wage gap varies with different characteristics of the workers, but, by estimating separate regressions for each sector, they point out that the gap tends to be higher for low-skilled workers.

Belchior and Bertussi (2016) also utilize a Brazilian data, similar to the one in this paper, and used the detailed available classifications on occupations and sectors in order to create broad classification for outsourced workers[1]. A Mincerian equation is estimated, in order to conclude that outsourced workers earn 7.2% to 10.5% less than non-outsourced ones. Furthermore, the authors examine if unobservable fixed effects bias the estimate, in a similar manner as Dube and Kaplan (2010); then, through a first difference model in panel data, come to the conclusion that a fixed bias does not significantly alter the previous estimation. An extensive analysis is carried, looking to identify average effects of outsourcing.

The authors argue that these wage disparities are motivated by differences in efficiency wage payments for outsourced and non-outsourced workers. This suggestion provides an explanation for the difference in rents uncovered by Dube and Kaplan (2010).

Goldshimidt e Schmieder (2017) also employed the previous methodology and estimated average impacts of outsourcing on German workers of logistics, food, security and cleaning (LFSC) sectors. They found that analyzed outsourced workers suffered a 9% wage penalty. These results are broadly consistent with previous estimates.

Despite that, they argue that it is difficult to account for different job characteristics of outsourced workers. The authors suggest using on-site outsourcing events as an identification strategy. They identify several aggregate flows of workers from final to intermediate firms in the LFSC's sectors. It is argued that these outsourced workers were likely to perform the same activities as they were previously doing.

Their estimates show that the workers who passed through such an event received between 10% and 15% less than similar workers who were not outsourced, ten years of the outsourcing event. Goldshimidt e Schmieder (2017) also employ the decomposition methodology employed by Card, Heining e Kline (2013) and conclude that differences in firm's rents explained all the declining relative wages of outsourced workers.

So, the previous studies consistently estimated negative average impacts of outsourcing on workers' wages and associated then with differences in non-competitive rents captured by those workers, relying mostly on fixed-effect estimates. These conclusions are congruent with recent empirical findings, derived from the works of Abowd, Kramarz and Margolis (1999), Card, Heining and Kline (2013) and Song et al. (2016).

Song et al. (2016), in particular, decomposed the variance of income and concluded that the most important fraction in the increased country inequality (more than two-thirds) is attributed to the increased inequality between firms, and not between workers in the same firm. Further yet, they show this process is mostly due to a larger segregation of workers in different companies.

They suggest outsourcing may be a relevant factor in explaining this process. However, they claim that simply dividing workers into more and less productive would not alter income distribution if they were paid in equivalence to their marginal productivity in both cases. In these terms, the uncovered difference in rents by difference outsource workers may help explaining these patterns in wage inequality.

This paper further explores the previous insights in mainly two dimensions. First, we develop a concrete theoretical explanation for the difference in rents appropriated by workers. Second, we systematically explore how outsourcing effects varies both theoretically and empirically for different workers.

[1] The work considers as outsourcing any type of service related to production and transferred to a third party. Thus, the database includes workers on different levels of human capital. For example, it considers consulting as a type of outsourcing.

3. Theoretical model

In this section, first Belchior and Bertussi (2016)'s model will be replicated, and then it will be expanded in order to incorporate more than one individual, as well as different sectors.

3.1 Base model

The economy under consideration has n identical workers whose preferences are represented by the utility function:

$$u = w - \varepsilon \tag{1}$$

where w is the wage perceived by the workers and ε indicates their level of effort. We will assume that the worker can perform on two levels of effort – high and low. The variable ε will assume value 1 if the worker performs on high effort, and value 0 if they perform on low effort.

Workers receive unemployment insurance of value $\overline{w}$ if they are not working, which acts as a reservation wage. Their effort is not perfectly observable. In case the effort is not being made, the employer observes this behavior with a probability of p. If the workers are caught shirking, they are fired.

The benefits are evaluated by the workers according to the expected utility theory. If they perform with high effort, ε assumes value 1, so they will not be submitted to uncertainty and their utility will be:

$$u^e = w - 1 \tag{2}$$

Conversely, if they show low effort their utility will be:

$$u^n = \overline{w} * p + (1 - p) * w \tag{3}$$

This way, it can be assured that the workers will exert effort if, and only if:

$$w \geq \overline{w} + \frac{1}{p} \tag{4}$$

We shall assume the economy contains only one final good, produced by m identical firms operating under perfect competition and with the objective function given by:

$$\pi = (1 + \delta\varepsilon) * S(n) - (C + w) * n, \quad \delta > 0 \tag{5}$$

where $S(n)$ is a strictly concave revenue function for the firms, n is the amount of workers hired and C represents costs associated to labor management (social charges, labor management costs, etc). It can be noted that when the workers make an effort (so that ε assumes a value of 1) the firms' revenue function is moved up by a positive factor $(1 + \delta)$, where δ is the increment factor of the revenue curve by effort.

It helps to define the derivative of the inverse revenue function as:

$$S'(n)^{-1} = \varphi(n) \tag{6}$$

One can easily understand that firms can maximize their profits in distinct states of nature, paying the efficiency wage or not. A firm may determine:

$$\max_n \pi = S(n) - (C + w) * n \tag{7}$$

$$s.a \qquad w \geq \overline{w}$$

in such a way as to not encourage workers to make an effort. In this case, we have:

$$n = \varphi(C + \overline{w}) \tag{8}$$

When the firm pays high enough salaries to induce workers to exert effort (so that ε assumes the value of 1), it will determine:

$$\max_{n^e} \pi^e = (1+\delta) * S(n^e) - (C + w) * n^e$$
$$(9)$$
$$s.a \qquad\qquad w \geq \overline{w} + \frac{1}{p}$$

Optimally, we have:

$$n^e = \varphi\left(\frac{C + \overline{w} + \frac{1}{p}}{1+\delta}\right) \tag{10}$$

If the shift in productivity is big enough, it will compensate the increase in wage costs, and firms will opt for paying the efficiency wage.

Now, an additional firm[2] that provides outsourced labor to the firms producing the final good is introduced. It is assumed to be more efficient than others in executing labor management, without incurring cost C. Additionally, said cost is supposed to be reduced to zero, in order to facilitate further mathematical development on the model.

The outsourcing firm pays a high enough wage to attract the workforce, and then passes it on to the other companies for a value w^o, in a similar outsourced labor supply model to the one proposed by Holmes e Snider (2011). It will receive unitary profit:

$$w^o - \overline{w} > 0 \tag{11}$$

An important point is that labor outsourcing firms have no incentive for paying the efficiency wage, since they cannot benefit directly from the increase in labor productivity, and it raises costs.

Now, firms can maximize their profit in three different states of nature, including the one where they hire outsourced labor:

$$\max_{n^t} \pi = S(n^t) - w^o * n^t \tag{12}$$

which gives us, optimally,

$$n^t = \varphi(w^o) \tag{13}$$

As with the efficiency wage case, the referred paper denotes that, for a sufficiently large cost reduction, the contracting of outsourced labor increases the profitability of firms. It also reduces the wage and productivity of workers, since they are not encouraged to deliver a high level of effort through the efficiency wage payment.

[2] The hypothesis that outsourcing firms operate as a monopoly is consistent with the work of Baccara (2007).

3.2 Various sectors

In this subsection, we will keep the hypothesis that workers are identical and that there is only one final good in the economy. It shall be assumed, however, that some firms have introduced exogenously a new supervision method, which makes it easier to observe the workers' effort[3]. This framework is hoped to mimic different grades of observation on the effort of workers from various sectors of an economy.

Supposing a fraction of the existing firms is able to observe the workers' effort with a probability of $\bar{p}$, so that:

$$\bar{p} > p \tag{14}$$

The problem for these firms when they induce workers to exert effort is:

$$\max_{n} \bar{\pi}^e = (1+\delta) * S(\bar{n}^e) - (C + w) * \bar{n}^e \tag{15}$$

$$s.a \qquad\qquad w \geq \overline{w} + \frac{1}{\bar{p}}$$

One can notice that, since it is easier for the employer to observe the worker's effort, the threat of resignation in case they do not make an effort becomes more believable. Therefore, the wage required to induce effort is lower than in the previous case.

Optimal contracting for this firm will imply:

$$(1+\delta) * S'(\bar{n}^e) = C + \overline{w} + \frac{1}{\bar{p}} \Rightarrow \bar{n}^e = \varphi\left(\frac{C + \overline{w} + \frac{1}{\bar{p}}}{1+\delta}\right) \tag{16}$$

In this case, the efficiency wage paid is lower and the impacts on productivity are the same, so we can conclude that these new firms are raising their profits more than the rest. Besides, it being shown to be profitable to apply efficiency wage for firms with more difficulty to observe effort, under the same assumptions it is also assuredly worth it for new firms to encourage workers' effort.

We now introduce again the possibility that the firm outsources labor. Noticeably, the firm's optimization when utilizing outsourced labor does not depend on how easily it can observe its workers' effort. Thus, the optimization performed by the firm and the optimal contracting of workers will be the same as those described in equations (12) and (13).

For a small enough w^o, it is possible that:

$$(1+\delta) * S(\bar{n}^e) - S(n^t) < \bar{n}^e * \left(C + \overline{w} + \frac{1}{\bar{p}}\right) - n^t * w^o \tag{17}$$

which ensures that profits from both types of firm will be greater in case they outsource labor. The addition of one more type of firm does not change the model's key characteristic, that outsourced workers do not receive efficiency wages.

The wage gap between outsourced and non-outsourced workers is defined as:

$$G = w - w^t \tag{18}$$

[3] Since they operate in a competitive market, an explicit short-term analysis will be conducted. This will make it possible for two companies with different production methods and cost functions to coexist in the market.

where w^t is the wage received by the outsourced workers. In the case of the original firms, the gap is:

$$G = \frac{1}{p} \tag{19}$$

As for the ones with the new supervision method, the wage gap is given by:

$$\bar{G} = \frac{1}{\bar{p}} \tag{20}$$

From that, given the restriction imposed by equation (14), we can guarantee that:

$$\frac{1}{\bar{p}} < \frac{1}{p} \Rightarrow \bar{G} < G \tag{21}$$

From this framework, one can observe a negative relationship between the increase in probability of detecting lack of effort in a sector and the wage gap in that same sector.

3.3 Various individuals

In this subsection, we go back to envisioning only one type of firm in the economy. Additionally, one more type of worker is brought in to the analysis. We shall now assume there is a fraction of high-skilled workers in this economy. These workers, as well as the low-skilled ones, can execute a high or low level of effort. Nevertheless, they will be assumed to be more productive and to bring a higher return rate for the firm from their effort. This will be inserted in the model, and ε will now assume values 1 and 2.

Such modeling allows productivity disparities of workers to be added to the model. Note that the individual incurs costs (in this case, higher effort) to increase their productivity, in a similar way to investment in human capital by individuals[4].

The firm is assumed to be capable of distinguishing high-skilled from low-skilled workers (those able to execute higher effort and be more productive, and those less able to do that). Nonetheless, it still cannot perfectly observe the level of effort achieved by individuals. So, it will observe with a probability of p whether a high-skilled individual is showing low effort (so that $\varepsilon = 1$) and dismiss them if that is the case.

When high-skilled individuals do not make an effort, their well-being is given by:

$$u_q^n = \overline{w} * p + (1 - p) * (w_q - 1) \tag{22}$$

and, when they do:

$$u_q^e = w_q - 2 \tag{23}$$

where subscript q indicates a reference to high-skilled workers.

Workers will exert effort if:

$$u_q^e \geq u_q^n \Rightarrow w_q \geq \overline{w} + \frac{1}{p} + 1 \tag{24}$$

[4] Despite the resemblance, we opted for not making the decision of investment in human capital endogenous, in order to keep the simplicity of the model.

Evidently, the required wage for high-skilled workers to exert effort is higher than the one required for the low-skilled, as stated in equation (4). This fits the empirical observation that high-skilled workers have a higher reservation wage (KRUEGER and MUELLER, 2016).

The new objective function for the firms is:

$$\pi = \left(1 + \delta\varepsilon_{nq}\right) * S\left(n_{nq}\right) + \left(1 + \delta\varepsilon_{q}\right) * S\left(n_{q}\right) - \left(C + w_{nq}\right) * n_{nq} - \left(C + w_{q}\right) * n_{q} \tag{25}$$

where subscript nq indicates a reference to low-skilled workers.

Supposing that

$$(1 + 2\delta) * S\left(n_q^e\right) - (1 + \delta) * S\left(n_q\right) > (C + \overline{w}) * \left(n_q^e - n_q\right) + n_q^e + \frac{n_q^e}{p} \tag{26}$$

is valid, it is ensured the firm will also pay efficiency wage to high-skilled workers. Therefore, the problem for firms is:

$$\max_{n_q^e, n_{nq}^e} \pi = \left(1 + \delta\varepsilon_{nq}\right) * S\left(n_{nq}\right) + \left(1 + \delta\varepsilon_{q}\right) * S\left(n_{q}\right) - \left(C + w_{nq}\right) * n_{nq} - \left(C + w_{q}\right) * n_{q}$$

$$\tag{27}$$

$$s.a \qquad w_{nq} \geq \overline{w} + \frac{1}{p}$$

$$w_q \geq \overline{w} + \frac{1}{p} + 1$$

The solving of the firm maximization problem yields:

$$S'\left(n_q^e\right) * (1 + 2\delta) = \overline{w} + \frac{1}{p} + 1 \Rightarrow n_q^e = \varphi\left(\frac{C + \overline{w} + \frac{1}{p} + 1}{1 + 2\delta}\right) \tag{28}$$

The optimal choice for low-skilled workers, in turn, is similar to the one obtained in equation (10). More productive workers receive higher wages than their low-skilled peers. In the model, this occurs because effort is more costly for productive individuals, and employers are willing to pay a higher wage in exchange for a bigger effort from them.

Now, the possibility of labor outsourcing by the firms will be introduced one more time, under the terms of the previous subsections. A firm that outsources labor has access both to high-skilled and low-skilled labor. It pays reservation wages to every type of individual, but renders its services to the firm producing the final good at distinct prices, so that high-skilled labor costs more than low-skilled labor. Keeping the premises from previous subsections and assuming that

$$(1 + 2\delta) * S\left(n_q^e\right) - (1 + \delta) * S\left(n_q^t\right) < n_q^e * (C + \overline{w} + \frac{1}{p} + 1) - n_q^t * w_q^o \tag{29}$$

where w_q^o represents the price of rendering high-skilled service to firms that produce the final good, we can assure the outsourcing of high-skilled workers is also efficient for firms.

Thus, the firm making the final good determines:

$$\max_{n_q^t, n_{nq}^t} \pi = S(n_{nq}^t) + (1+\delta) * S(n_q^t) - w_q^o * n_q^t + w_{nq}^o n_{nq}^t \tag{30}$$

which gives:

$$S'(n_q^t) * (1+\delta) = w_q^o \Rightarrow n_q^t = \varphi\left(\frac{w_q^o}{1+\delta}\right) \tag{31}$$

The optimal amount of low-skilled outsourced workers hired is similar to that obtained in equation (13).

By using the definition of wage gap, specified in equation (18), we find the gap for low-skilled workers to be identical to the one shown in equation (19). On the other hand, for high-skilled workers,

$$G^q = \frac{1}{p} + 1 \tag{32}$$

infers that

$$\frac{1}{p} + 1 > \frac{1}{p} \Rightarrow G^q > G^{nq} \tag{33}$$

We therefore conclude that the gap between outsourced and non-outsourced workers must be larger for high-skilled individuals than for low-skilled individuals.

4. Empirical analysis

Our model yields two clear empirical predictions. First, we expect that the wage gap of outsourced workers will be higher for more productive workers - witch contradicts some of the insights provided by previous papers. Second, our model predicts that the gap will be greater in sectors where it is difficult to observe effort.

In the following sections we will analyze only the first empirical prediction of our theoretical model. As will be discussed in subsection 4.2, we can use occupation and sector detailed classifications to identify which workers are outsourced, but we frequently cannot tell which final firms effectively employ the worker. This prevents us from testing the second prediction above.

4.1 Econometric model

Seeking to test the model's predictions, the following mincer equation will be estimated first:

$$\ln(w_i) = \alpha T_i + \boldsymbol{X_i \beta} + u_i \tag{34}$$

We take the natural logarithm of the wage of individual i (w_i) as function of a variable that indicates whether the worker is outsourced (T_i) and a vector of control variables ($\boldsymbol{X_i}$). We wish to assess whether outsourced workers earn less, once relevant cofactors are controlled, such as the previously reviewed empirical studies did.

Next, the quantile regression framework will be used to examine wage distribution among individuals, conditional to outsourcing and other cofactors in several quantiles of earning distribution. Let:

$$\ln(w_i) = y_i \tag{35}$$

and

$$\alpha T_i + \boldsymbol{\beta X_i} = \boldsymbol{z_i} \tag{36}$$

Formally, the quantile regression will be estimated by:

$$\min_{\boldsymbol{\beta},\boldsymbol{\alpha}} \sum_{i:y \geq z} \theta * |\ln(w_i) - \alpha T_i - \boldsymbol{\beta X_i}| + \sum_{i:y \leq z} (1-\theta) * |\ln(w_i) - \alpha T_i - \boldsymbol{\beta X_i}| \tag{37}$$

where θ indicates the quantile of analysis. We obtain a coefficient vector that minimizes the equation in the desired quantiles and corresponds to the conditional mean of the variables of interest in the quantile θ (KOENKER and BASSET, 1978; KOENKER and HALLOCK, 2001). This analysis will allow a very detailed decomposition of how outsourcing affects the wages of workers with different productivities. This has not been achieved yet, in any Brazilian or international study.

4.2 Database

We will employ micro-data from the Annual Social Information Report (RAIS) for 2014. This data is annually reported for nearly all formal firms in Brazil and used it is used for social security purposes. The misreport of information is subject to penalty, so most firms use specialist accountants to register the information (ALVAREZ et al, 2017).

RAIS contains information on several demographical characteristics of individuals and some characteristics of the firm in which he is employed. Despite that, the database does not divide the information for outsourced and non-outsourced workers. In order to overcome this issue, we use the method suggested by Dube e Kaplan (2010) for the CPS in the U.S.

Said method has been proposed by Belchior e Bertussi (2016) and consists of cross-linking data from the Brazilian Classification of Occupations (CBO) and the National Classification of Economic Activity (CNAE). They take advantage of the specificity of those classifications and identify outsourced workers in a very broad selection of sectors.

Also, we will use a identified version of the database, provided by the Work and Employment Ministry (MTE) for the purpose of research. This particular version of the database contains information that allow us to identify firms and individuals across time.

Thereby, we will initially be working with about 50 million observations in the database, the size of the Brazilian formal sector. Nonetheless, we could not use it entirely, as the estimation of the quantile regression (described in the last subsection) becomes computationally unfeasible with that number of observations. In order to solve this problem, we created a random sub-sample with 250 thousand observations[5] from the original database. The process to attain this sub-sample is described in Appendix II.

4.3 Description of the Variables

Our dependent variable is the natural logarithm of employee remuneration in December 2014[6]. In opposition to prior estimates, which used the average workers' remuneration along the year, we chose to use just the remuneration for the last month of the year. That is because the statements that compose the database are given by employers, and they tend to fill in recent information more accurately (RAMOS, 2012).

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[5] Once it became evident that the quantile regression estimation would not be feasible with the full sample, we created several random samples with reduced number of observations. Starting with one million, we progressively diminished the sample until it became estimable, at a number of 250 thousand observations. We performed the regressions on Table 1 with our random sub-sample, and results were very similar to those found using the entire database. Besides, as will be detailed in the next section, this sub-sample is large enough to make sure all the estimated coefficients are significant to the level of 1% in any of the quantiles.

[6] Workers who were dismissed throughout the year were excluded from the sample.

The control vector is formed by the following variables: education; age (on level and squared); experience in the firm the worker is employed at (on level and squared); geographic region they live in; sector they work in; gender; ethnicity; and size of reported establishment.

The education variable, measured by the maximum level of instruction achieved, aims to control the individuals' difference in productivity[7]. According to human capital theory, prevalent in the explanation of individuals' varying remunerations, this should be a very relevant factor to the observed wage variation (BECKER, 1975).

The adding of age and experience at current job variables, used as proxy for the individual's experience in the work market, seeks to identify the presence of specific human capital, acquired with time in the job. A quadratic term was included to detect non-linear relationships within the experience-wage relation, since the productivity gains generated are exhausted over time (ARROW, 1962). The variables are measured in months and point to how long the individual has worked for the same company.

Binary variables are added to control regional segmentations in wage determination or discrimination patterns against minorities. The Northeast region was taken as reference and dummy variables were assigned for the other regions. The ethnicity binary variable assumes value 1 if the individual is white, and value 0 if they belong to any other ethnic group. We also used a binary variable to identify outsourced and non-outsourced workers, according to the classification discussed in the last subsection.

At last, we added establishment size to the regression as an indicator for the propensity of the individual to receive an efficiency wage (OI and IDSON, 1999). The size of the company is defined by the number of workers, according to the rating recommended by SEBRAE (2013) when using data from RAIS[8].

4.4 Results

In Table 1, an estimation of equation (34) is performed. In model (1), we only perform the regression of the wage logarithm's variable as a function of the outsourcing dummy variable. In model (2), are included in the regression controls of education, experience (on level and squared) and age – consistent with human capital theory, without discrimination or segmentation in the labor market. Ultimately, in model (3) all aforementioned variables are included.

	Model (1)		Model (2)		Model (3)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.297***	0.0004	-0.130***	0.0003	-0.136***	0.00042
Education	-	-	0.185***	0.00005	0.165***	0.00006
Experience	-	-	0.0039***	0.00000	0.0033***	0.00000
$Experience^2$	-	-	-0.00004***	0.00000	-0.00003***	0.00000
Age	-	-	-0.0084***	0.00000	0.0089***	0.00001
Firm size	-	-	-	-	0.116***	0.00008
Male	-	-	-	-	0.250***	0.00019
White	-	-	-	-	0.076***	0.00019
Occupational dummy	no	-	no	-	yes	-
Regional dummy	no	-	no	-	yes	-

Table 1 – Results of the Mincerian Regression (34) through GLS

Note: The statistic significance of the estimated coefficient is indicated by the number of asterisks: * indicates 10% significance, ** indicates 5% significance and *** indicates 1% significance.

One can observe that, in all models, the control variable coefficient presents the sign expected by literature. Moreover, all of them present statistic significance of 1%.

[7] Levels of instruction are: incomplete primary school, complete primary school, incomplete secondary school, complete secondary school, incomplete superior education, complete superior education, master's degree, doctoral degree.

[8] Our variable assumes four levels: Microenterprise (up to 9 employees), small enterprise (10 to 49 employees), medium enterprise (50 to 99 employees) and big enterprise (more than 100 employees).

In the first model, outsourced workers were estimated to earn approximately 34%[9] less than non-outsourced ones. In model (2), we see that most of this penalty can be explained by the addition of control variables. The wage difference estimated in the second model is 13.8%. In model (3), after adding the whole vector of control variables, the estimation for the gap goes up again, to 14.6%.

The estimation pattern is consistent with that attained by Brazilian studies, which assessed the impact of outsourcing on wage; but the estimates for the gap are higher in all three models and closer to the ones achieved by international work.

In Table 2 are arranged the results of the estimation of equation (37) for quantiles 0.1, 0.5 and 0.9. The results for the quantile regression in the other quantiles are available in Appendix III[10].

	Quantile (0.1)		Quantile (0.5)		Quantile (0.9)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.074***	0.00482	-0.117***	0.00514	-0.148***	0.01
Education	0.064***	0.00076	0.129***	0.00081	0.237***	0.0016
Experience	0.002***	0.00004	0.003***	0.00004	0.004***	0.00009
$Experience^2$	-0.00003***	0.00000	-0.00003***	0.00000	-0.00005***	0.00000
Age	0.0038***	0.0001	0.006***	0.00011	0.015***	0.0002
Firm size	0.054***	0.00098	0.103***	0.00104	0.157***	0.00215
Male	0.116***	0.00222	0.239***	0.00236	0.350***	0.0048
White	0.031***	0.00232	0.058***	0.00247	0.109***	0.00501
Occupational dummy	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-

Table 2 – Results of the quantile regression (37) for quantiles 0.1, 0.5 (medium regression) and 0.9.

In order to synthesize the results of these estimates, Chart 2 illustrates the estimated coefficient for the percentage impact of outsourcing on wages in each quantile.

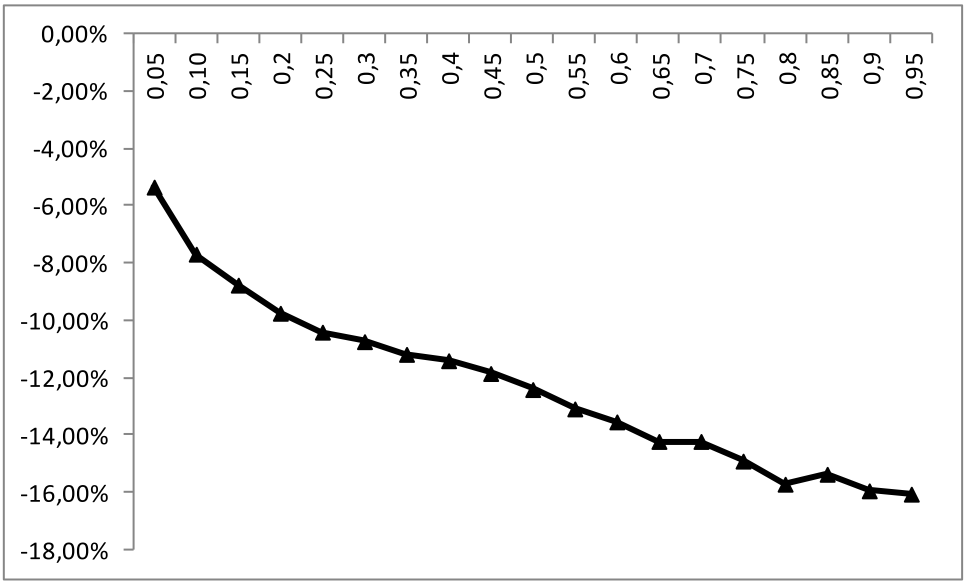

Chart 1 – Marginal impact of outsourcing on individuals' wage by income quantile.

We can see that the estimated values for outsourcing are negative in all of the quantiles, and the negative impact of outsourcing becomes progressively larger according to the income. Such estimates provide empirical support to our model's prediction that more productive workers (and, consequently, with higher wages) suffer relatively more with outsourcing than less productive ones.

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9 To register our results we used the following correction for the coefficients: $R = (e^{\beta} - 1) * 100$.

10 Quantile regressions were estimated from quantile 0.05 to quantile 0.95 with intervals of 0.05 between them.

5. Endogeneity bias

It is possible that there is some form of unobserved characteristics not orthogonal to the occupational status that drove our previous results. This section tries to account for that.

5.1 New Database

In this section we use a confidential version of the RAIS database, described in subsection 4.2, for the years of 2009 and 2010. Unlike the previous database, this version contains an individual unique identifier for all workers, which allow us to follow each individual in time.

Instead of working with all individuals, we restrict the database in 2010 only to those individuals who were outsourced (defined in the same way as described in section 4), obtaining approximately four and a half million observations.

Then, we match those individuals with the database for the previous year. We have been able to match a little less than four million individuals, approximately 86,7% of all outsourced workers in 2010[11]. In this subsample, around one and a half million individuals were not outsourced in 2009.

Since all the workers in the new database were outsourced in 2010, we expect that all the individuals in this subsample will have much similar characteristics and, therefore, the workers who were outsourced in 2010 and were not in 2009 constitute a much better counter-factual than the one used in the previous section. Next, we will re-estimate some of the previous equations with our new database.

5.2 Results

In table 3, we present the results for our estimates for equation (34), similar to those displayed in table 1, for our new database:

	Model (1)		Model (2)		Model (3)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.041***	0.0008	-0.074***	0.0007	-0.076***	0.0007
Education	-	-	0.181***	0.00002	0.1754***	0.0002
Experience	-	-	0.0041***	0.00000	0.0044***	0.00000
Experience^2	-	-	-0.00004***	0.00000	-0.00003***	0.00000
Age	-	-	-0.008***	0.00000	0.0078***	0.00001
Firm size	-	-	-	-	0.027***	0.00008
Male	-	-	-	-	0.281***	0.00019
White	-	-	-	-	0.091***	0.00019
Occupational dummy	no	-	no	-	yes	-
Regional dummy	no	-	no	-	yes	-

Table 3 – Results of our GLS regression (34) using our new sample

We can see that the raw gap between outsourced workers is drastically smaller in model (1) of table 3 than the estimated in table 1 – only -4,2%. Once we add additional control variables, the estimated gap increases to approximately -7,9%, which is still smaller than the respective models in table 1. This results points out that, in fact, unobserved characteristics seem to explain a large part of the outsourced wage gap.

Next we re-estimate equation (37)[12] for our database for quantiles 0.1, 0.5 and 0.9. The results are presented in Table 4.

[11] The non matched workers were not in the formal market in 2009. The rate of matched individuals achieved with this procedure is very similar to the matching using all formal workers done by Belchior and Bertussi (2016).

[12] Again, the estimation of the quantile regression was not computationally feasible even with the drastic reduction of the new database size. Therefore, we applied the same method described in apendix II to obtain a new random subsample of our new database.

	Quantile (0.1)		Quantile (0.5)		Quantile (0.9)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.0150***	0.0021	-0.0788***	0.0025	-0.1208***	0.0056
Education	0.0506***	0.0006	0.1765***	0.0007	0.2288***	0.0017
Experience	0.0014**	0.00004	0.0044***	0.00005	0.0066***	0.0001
Experience^2	-0.00003***	0.00000	-0.00003***	0.00000	-0.000009***	0.00000
Age	0.0012***	0.00009	0.0078***	0.00011	0.0115***	0.0002
Firm size	0.0043***	0.0009	0.0288***	0.0010	0.0514***	0.0023
Male	0.0962***	0.0019	0.2896***	0.0022	0.3782***	0.0050
White	0.0273***	0.0017	0.0937***	0.0021	0.1161***	0.0046
Occupational dummy	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-

Table 4 – Results of the quantile regression (37) for quantiles 0.1, 0.5 (medium regression) and 0.9 in our subsample.

First, we note that, when we control for selection bias, the wage gap is still negative and statistically significant at the one percent level for the three quantiles. The magnitude of the wage gap, however, is smaller than the previous in all three estimates – also indicating the importance of unobservable effects. This effect seems to be relatively stronger for low productive workers as the estimation for the (0.1) quantile got severely closer to zero and the estimation for the (0.9) quantile was much closer to the original result.

In Chart 2, we present the estimates for the marginal impact of outsourcing on wages on each quantile in order to summarize our results. Also, for comparative purposes, we plot the previous results for the quantile regression displayed in Chart 2.

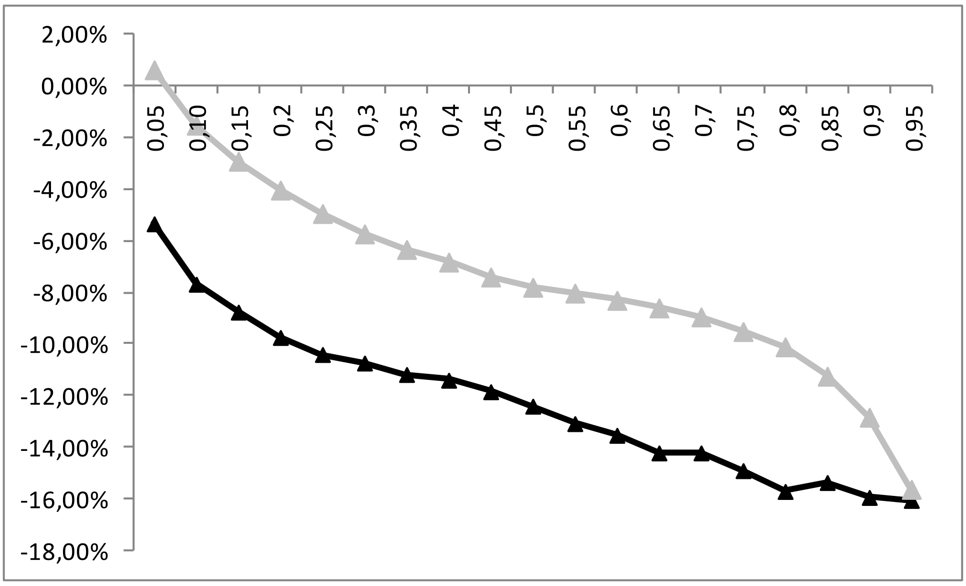

Chart 2 – Marginal impact of outsourcing on individuals' wage by income quantile in the subsample (gray) and previous quantile regression results as a baseline (black)

The graph confirms the previous conclusions drawn from Table 4. The entire distribution was dragged up as we controlled for the unobservable characteristics. The effect, of course, is not the same for different individuals. The coefficient for the poorest workers is slightly positive, despite not economically or statistically significant, while for the richer individuals the coefficient is statistically indifferent for our previous estimates. We argue that there must be unobservable individual characteristics, undesirable from the viewpoint of the employer, that affect the occupational status of the workers. Although this characteristics seem to be present in all distribution, they appear to be far more important for the less productive individuals. The complete set of estimates for the quantile regression are displayed in appendix III.

6. Conclusion

This paper aimed to assess distinct impacts of outsourcing on different groups of workers. When reviewing the literature on the theme, we noticed few studies have made an evaluation of the consequences of outsourcing for different groups of workers, whereas none have made systematic differentiations by workers or by income.

We built a theoretical model that expands the framework developed by previous works, to an economy with more than one sector and more than one type of worker. The model suggests the gap between outsourced and non-outsourced workers must be larger for more productive workers, as well as for those who work at sectors where effort observation is harder.

Next, we used RAIS's 2014 micro-data, along with a similar procedure to the one suggested by Dube e Kaplan (2010) to distinguish outsourced and non-outsourced workers. Starting by conducting estimates on the average impact of outsourcing on wages, we concluded that once all control variables are used, outsourced workers earn about 14.5% less than their counterparts. Values found are higher than previously estimated for Brazil, becoming closer to American and European estimates.

Then, a quantile regression was conducted to evaluate the impact of outsourcing on workers with different income levels (and therefore different productivities). It concluded that the impact of outsourcing on wages grows progressively with income, as suggested by the theoretical model.

Clearly the previous results might be driven by an unobservable form of selection. Trying to deal with that, we use a confidential version of the RAIS database for the years of 2009 and 2010. We restrict our sample to individuals in 2009 who could be matched across years and were outsourced in 2010 sample. Since a lot of those individuals weren't outsourced in 2009 we are able to build a much similar control group for our analysis.

Once we re-estimated our basic model with our new database, we found the the wage gap was significant smaller when we controlled for unobserved characteristics – about 7,9%. Finally, we re-estimated the quantile regression using our new subsample. Our results for the wage gap tend to get near zero. This seem to be especially true for low productive workers. For the poorer workers in our dataset, for example, we obtained an estimate statistically indifferent from zero while the previous result indicated a wage penalty of almost 6%. Alternatively, for the most productive workers the estimates for the wage gap are similar with the previous results, around 15%. Still, the results get progressively bigger as the worker's income grows, which is consistent with our model. Overall, this paper suggests that outsourcing tends to have negative impact on the wages of a great variety of workers. In addition, the segmentation of the analysis endorses the efficiency wage model suggested in this study.

7. References

Abowd, John M., Francis Kramarz and David N. Margolis. 1999. High wage workers and high wage firms. *Econometrica* 67, no. 2: 255-333.

Alvarez, Jorge; Felipe Benguria, Niklas Engbom e Christian Moser (2017). Firms and the decline of earnings inequality in Brazil. *Working Paper*.

Arrow, Kenneth J. 1962. The economic implications of learning by doing. *The Review of Economic Studies* 29, no. 3: 155-173.

Baccara, Mariagiovanna. 2007. Outsourcing, information leakage and Consulting firms. *The RAND jornal of economics* 38, no.1:269-89.

Becker, Gary S.1975. *Human capital: a theoretical and empirical analysis with special reference to education*. National Bureau of Economic Research.

Belchior, Carlos Alberto Doria Carneiro and Geovana Lorena Bertussi. 2016. Outsourcing and efficiency wages: the case of Brazil. 44º brazilian annual economic meeting - ANPEC. Avaliable at: https://www.anpec.org.br/encontro/2016/submissao /files_I/i13-10cb07e200cbcd5a6abc7ac504615013.pdf.

Berlinski, Samuel. 2008. Wages and contracting out: does the law of one price hold? *British Journal of Industrial Relations* 46, no.1:59-75, 2008.

Card, David, Jörg Heining and Patrick Kline. 2013. Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics* 128, no.3:967-1015.
Dube, Arindrajit and Ethan Kaplan. 2010. Does outsourcing reduce the wages in low wages service occupations? Evidence from janitors and guards. *Industrial and Labour Relations Review* 63, no.2: 287-306.
Goldschmidt, Deborah e Johannes Schmieder. 2017. The rise of domestic outsourcing and the rise of German wage structure. *The Quarterly Journal of Economics*, forthcoming.

Koenker, Roger, and Gilbert Basset Jr. 1978. Regression quantiles. *Econometrica*, 46, no.1: 33-50.
Koenker, Roger, and Kevin F. Hallock. 2001. Quantile regression. *Journal of Economic Perspectives* 15, no.4: 143-156.
Krueger, Alan B., and Andreas I. Mueller. 2016. A contribution to the empirics of reservation wages. *American Economic Journal: Economic Policy*, 8, no:1:142-79.
Mankiw, Gregory and Phillip Swagel. 2006. The politics and economics of offshore outsourcing. *Journal of monetary economics*, 53, no.5, p.1027-56.
Oi, Walter Y., and Todd L. Idson. 1999. Firm size and wages. In *Handbook of Labour Economics*, ed. David Card and Orley Ashenfelter. Elsevier.
Ramos, Carlos Alberto. 2012. *Economia do Trabalho: modelos teóricos e o debate no Brasil*. CRV, Brasília.
SEBRAE. 2013. Anuário do trabalho na micro e pequena empresa. Avaliable at: http://www.sebrae.com.br/Sebrae/Portal%20Sebrae/Anexos/Anuario%20do%20Trabalho%20Na%20Micro%20e%20Pequena%20Empresa_2013.pdf.
Stein, Guilherme.; Eduardo Zylberstajn and Hélio Zylberstajn. Diferencial de salários da mão de obra terceirizada no Brasil. *São Paulo School of economics working paper*, n.4, 2015.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom and Till von Wachter. 2016. Firming up inequality. *National Bureau of Economic Research Working Paper*, no.21199.
Williansom, Oilver. 2008. Outsourcing: transaction costs economics and supply chain management. *Journal of supply chain management*, 44, no.2: 5-16.

7. Appendix I – Making of the database

The following table, developed by Belchior and Bertussi (2016), indicates the occupations commonly considered as outsourced, as well as the sectors associated to them, implying the worker's occupational status.

Administrative Workers			Professions	CBO	CNAE
Professions	CBO	CNAE	Barman	513420	56201
Directors of several areas	1231	82113	Food producer and assistant	5135	56201
	1232			5136	
	1233		Residencial sector		
	1234		Profissões	CBO	CNAE
	1238		Elevator operator	5141	81214
Lawyers	2410	82113	Cleaner	5142	81214
		70204		5143	
		69117	Security agent	5172	80111
Accountants	3511	82113		5173	
	252210	69206	Doorman	5174	81117
		70204			81214
IT and R&D					80111
Professions	CBO	CNAE	Eletricity Sector		
Directors and workers of R&D and IT	1236	73114	Professions	CBO	CNAE
	1237	82113	Eletricity Sector workers	9511	951
	1425	631		7313	
	1426	620		7321	952
		73203		7311	
		70204		7156	63992
Administrators and network analysts	2123	95118		7243	
		82202		7301	61096
		82113		8601	
	2124	63119		9501	43215
		620		9502	
		631		9531	33210
Programmers	3171	95118		9541	
		70204	Civil construction sector		
		620	Professions	CBO	CNAE
		631	Manual laborers and builders	7151	71120
Telemarketing workers	4223	82202		7152	
	4222			7153	
	420135			7154	
Maintenance				7155	
Professions	CBO	CNAE		7157	
Maintenance technicians	3141	43223		7161	
		28691		7162	43991
	3144	33147		7163	
				7164	
Mechanics and maintenace specialists	9151	33121		7165	
		33147		7166	
	9153	61906		7170	
		43215		7201	43215
Food Sector				7202	
Professions	CBO	CNAE		7211	
Cook	5132	56201		7212	
Server	513425	81214		7241	
	513430	56201		7243	

8. Appendix II – Creation of a Random Sub-sample

The random sub-sample was created using the pseudo-random number generator KISS, available in the 13th version of statistic software Stata. To carry out this procedure, first the seed s was established in order to allow the replication of the randomization process. The seed used was 45002494 in the first quantile regression and 98173938 for the second.

Next, we attributed a random value to each observation in the database, extracted from a uniform distribution with extreme values 0 and 1:

$$X \sim U(0,1)$$

Subsequently, the samples from the database were rearranged in ascending order according to the value attributed to them, from the previous distribution. Finally, the random sub-sample was defined as the first 250 thousand observations from the database after the rearrangement. The full sequence of commands is:

```
set seed s
gen random=runiform()
sort random
gen insample=_n <= 250000
```

9. Appendix III – Full results of the quantile regression

Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Quantile	Quantile (0.05)		Quantile (0.15)		Quantile (0.20)		Quantile (0.25)	
Outsourced	-0.052***	0.00716	-0.084***	0.00457	-0.093***	0.00421	-0.099***	0.0044
Education	0.063***	0.00113	0.071***	0.00072	0.079***	0.00066	0.087***	0.00069
Experience	0.001***	0.00006	0.002***	0.00004	0.002***	0.00003	0.002***	0.00004
Experience^2	-0.00004***	0.00000	-0.00003***	0.00000	-0.00003***	0.00000	-0.00003***	0.00000
Age	0.0047***	0.00015	0.0038***	0.00009	0.0041***	0.00009	0.0043***	0.00009
Firm size	0.040***	0.00145	0.063***	0.00092	0.071***	0.00085	0.077***	0.00089
Male	0.114***	0.00329	0.132***	0.0021	0.148***	0.00193	0.163***	0.00202
White	0.028***	0.00344	0.036***	0.00219	0.039***	0.00202	0.043***	0.00212
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.3)		Quantile (0.35)		Quantile (0.4)		Quantile (0.45)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.102***	0.00444	-0.106***	0.00464	-0.108***	0.00475	-0.112***	0.00488
Education	0.096***	0.0007	0.103***	0.00073	0.112***	0.00074	0.120***	0.00075
Experience	0.002***	0.00004	0.003***	0.00004	0.003***	0.00004	0.003***	0.00004
Experience^2	-0.00003***	0.00000	-0.00003***	0.00000	-0.00003***	0.00000	-0.00003***	0.00000
Age	0.0047***	0.00009	0.0052***	0.00009	0.0057***	0.0001	0.0063***	0.0001
Firm size	0.083***	0.009	0.088***	0.00094	0.093***	0.00096	0.098***	0.00099
Male	0.178***	0.00204	0.193***	0.00213	0.208***	0.00216	0.223***	0.00224
White	0.046***	0.00213	0.048***	0.00223	0.050***	0.00228	0.053***	0.00234
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.55)		Quantile (0.6)		Quantile (0.65)		Quantile (0.7)	
Outsourced	-0.123***	0.00539	-0.127***	0.00567	-0.133***	0.00597	-0.133***	0.00652
Education	0.139***	0.00085	0.149***	0.00089	0.159***	0.00094	0.171***	0.00102
Experience	0.003***	0.00005	0.003***	0.00005	0.003***	0.00005	0.004***	0.00006
Experience^2	-0.00003***	0.00000	-0.00004***	0.00000	-0.00004***	0.00000	-0.00004***	0.00000
Age	0.0075***	0.00011	0.0082***	0.00012	0.0090***	0.00012	0.010***	0.00013
Firm size	0.0108***	0.00109	0.113***	0.00115	0.119***	0.00121	0.124***	0.00132
Male	0.254***	0.00258	0.286***	0.00261	0.281***	0.00274	0.293***	0.003
White	0.061***	0.00249	0.065***	0.00273	0.069***	0.00287	0.076***	0.00313
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.75)		Quantile (0.8)		Quantile (0.85)		Quantile (0.95)	
Outsourced	-0.139***	0.00709	-0.146***	0.00775	-0.143***	0.00896	-0.149***	0.01413
Education	0.183***	0.00111	0.197***	0.00122	0.216***	0.00141	0.266***	0.00229
Experience	0.004***	0.00006	0.004***	0.00007	0.004***	0.00008	0.003***	0.00013
Experience^2	-0.00004***	0.00000	-0.00005***	0.00000	-0.00005***	0.00000	-0.00005***	0.00000
Age	0.0111***	0.00015	0.0122***	0.00016	0.0137***	0.00019	0.018***	0.0003
Firm size	0.0131***	0.00144	0.138***	0.00157	0.145***	0.00182	0.165***	0.00287
Male	0.308***	0.00326	0.323***	0.00356	0.341***	0.00412	0.272***	0.00649
White	0.082***	0.00341	0.091***	0.00372	0.100***	0.00431	0.112***	0.00672
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-

Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Quantile	Quantile (0.05)		Quantile (0.15)		Quantile (0.20)		Quantile (0.25)	
Outsourced	0.0064	0.0042	-0.0287***	0.0020	-0.0395***	0.0020	-0.0482***	0.0020
Education	0.0606***	0.0013	0.0567***	0.0006	0.0667***	0.00063	0.0754***	0.00064
Experience	0.0017***	0.00009	0.0016***	0.00004	0.0019***	0.00004	0.0021***	0.00004
Experience^2	-0.00002***	0.00000	-0.00001***	0.00000	-0.00001***	0.00000	-0.00001***	0.00000
Age	0.0018***	0.0001	0.0011***	0.00008	0.0013***	0.00008	0.0017***	0.00008
Firm size	0.000005	0.0017	0.0068***	0.00085	0.0089***	0.00085	0.077***	0.00089
Male	0.1325***	0.0037	0.1033***	0.0018	0.1205***	0.0018	0.163***	0.00202
White	0.0291***	0.0035	0.0339***	0.0016	0.0406***	0.0016	0.043***	0.00212
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.3)		Quantile (0.35)		Quantile (0.4)		Quantile (0.45)	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Outsourced	-0.0557***	0.0022	-0.0614***	0.0021	-0.066***	0.0022	-0.0714***	0.0024
Education	0.0831***	0.00068	0.0900***	0.00066	0.0973***	0.00071	0.1053***	0.00075
Experience	0.0022***	0.00004	0.0023***	0.00004	0.0024***	0.00004	0.0026***	0.00005
Experience^2	-0.00001***	0.00000	-0.00004	0.0002	-0.00004*	0.00002	-0.00001***	0.00000
Age	0.0020***	0.00009	0.0022***	0.00008	0.0026***	0.00009	0.0031***	0.0001
Firm size	0.0120***	0.009	0.0142***	0.00089	0.0148***	0.00096	0.0162***	0.0010
Male	0.157***	0.0019	0.1742***	0.0019	0.1916***	0.0020	0.2083***	0.0021
White	0.0499***	0.0018	0.0542***	0.0017	0.0566***	0.0018	0.0612***	0.0020
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.55)		Quantile (0.6)		Quantile (0.65)		Quantile (0.7)	
Outsourced	-0.772***	0.0027	-0.0798***	0.0029	-0.0825***	0.0032	-0.0857***	0.0036
Education	0.1237***	0.00087	0.1334***	0.0009	0.144***	0.0010	0.1564***	0.0011
Experience	0.003***	0.00006	0.0033***	0.00005	0.0037***	0.00007	0.0042***	0.00008
Experience^2	-0.00002***	0.00000	-0.00001***	0.00000	-0.00009***	0.00003	-0.00005	0.00003
Age	0.0042***	0.00011	0.0048***	0.00012	0.0055***	0.0001	0.0063***	0.00015
Firm size	0.0198***	0.0011	0.0215***	0.0012	0.0249***	0.0013	0.0288***	0.0015
Male	0.2437***	0.0024	0.2631***	0.0026	0.2827***	0.0029	0.3022***	0.0032
White	0.0688***	0.0023	0.0741***	0.0024	0.0799***	0.0027	0.0848***	0.0029
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-
Quantile	Quantile (0.75)		Quantile (0.8)		Quantile (0.85)		Quantile (0.95)	
Outsourced	-0.0909***	0.0039	-0.0963***	0.0043	-0.1066***	0.0049	-0.1453***	0.0076
Education	0.1710***	0.0012	0.1861***	0.0013	0.2046***	0.0015	0.2641***	0.0023
Experience	0.0047***	0.00008	0.0054***	0.00009	0.006***	0.0001	0.0069***	0.00017
Experience^2	-0.00002***	0.00000	-0.00004***	0.00000	-0.00007***	0.00000	-0.00001***	0.00000
Age	0.0074***	0.00015	0.0083***	0.00018	0.0098***	0.0002	0.0145***	0.0003
Firm size	0.0334***	0.0016	0.0385***	0.0018	0.0447***	0.0020	0.0572***	0.0032
Male	0.3241***	0.0035	0.3444***	0.0038	0.3616***	0.0044	0.4036***	0.0068
White	0.0910***	0.0032	0.0984***	0.0036	0.1069***	0.0040	0.1215***	0.0063
Occupational dummy	yes	-	yes	-	yes	-	yes	-
Regional dummy	yes	-	yes	-	yes	-	yes	-