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Effect of technological innovation and diffusion on the interindustry mobility of Brazilian workers☆

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Abstract

This paper aims to investigate the effects of investment in industrial R & D on the mobility of workers between firms and/or industrial sectors in Brazil, considering that the technological gap between the sectors can reduce the propensity for interindustrial labor mobility. Using panel data for the period 2003–2008, constructed from microdata RAIS-Migra and industry data from the Brazilian Technological Innovation Survey (PINTEC), the Annual Industrial Survey (PIA) and input–output matrices, we estimate a multinomial logit model with random intercepts (GLLAMM – Generalized Linear Latent and Mixed Models). The main results show that the technological diffusion increases the chances of changing jobs, the technological variables have greater importance for unskilled workers than for skilled, and among non-intensive technology industries, the technological innovation can have positive impact on interindustrial mobility.

Keywords: Technological innovation; Technological diffusion; Mobility of workers; Multinomial logit; GLLAMM

Resumo

Esse artigo tem por objetivo investigar os efeitos do investimento em P&D industrial sobre a mobilidade de trabalhadores entre firmas e setores industriais brasileiros, considerando que a distância tecnológica entre os setores pode reduzir a propensão à mobilidade intersetorial de trabalhadores. Com o uso de um painel de dados para o período de 2003–2008, construído a partir de microdados da RAIS-Migra e de dados setoriais provenientes da Pesquisa de Inovação Tecnológica (PINTEC), da Pesquisa Industrial Anual (PIA) e de matrizes de insumo-produto estimou-se o modelo logit multinomial com interceptos aleatórios (GLLAMM - Generalized Linear Latent and Mixed Models). Os principais resultados obtidos mostram que: a difusão tecnológica aumenta as

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chances de mudança de emprego; variáveis tecnológicas possuem maior importância para os trabalhadores não qualificados do que para os qualificados; e, entre os setores não intensivos em tecnologia, uma inovação pode ter impacto positivo sobre a mobilidade intersetorial.

Palavras-chave: Inovação tecnológica; Difusão tecnológica; Mobilidade de trabalhadores; Logit multinomial; GLLAMM

1. Introduction

The mobility of labor is a means of acquiring technological knowledge to the recipient firm (Song et al., 2003). As part of technological knowledge is tacit in nature, lying embodied in the individual, labor mobility is also a channel of knowledge spillover, from which the receiving firm takes advantage of (Feldman, 1999; Hall et al., 2010; Marilanta et al., 2009). From this viewpoint, the mobility of workers influences the activity of R & D.

On the other hand, there is little evidence in the opposite direction, considering the investment in R & D, and technological progress in the sector, as a possible cause of the propensity to mobility of workers between firms, or even between sectors. Based on Magnani (2009), it is assumed the hypothesis that the larger the technological distance between the industries, smaller is the possibility of interindustrial transfer of workers, as the distance of technology between companies and industries is related to the cumulative amount of individual's specific human capital. In this sense, once transferred from one job to another, the individual cannot adapt to the requirements in terms of skills, of the new job.

Magnani (2009) is one of the few empirical studies that investigate this direction of causality, bringing evidence to the United States. Furthermore, the purpose of this article is to extend this body of evidence for cases related to developing countries such as Brazil, which has peculiarities in its sectoral trajectories of technological development, marked by industrialization for the domestic market, technological dependence on developed countries, imports of capital goods and relatively large weight of multinational firms in more technologically advanced sectors (Viotti, 2002; Viotti et al., 2005; Queiroz and Carvalho, 2005; De Negri et al., 2005.).

In this sense, more technologically mature industries have relatively large weight in the industrial structure of countries like Brazil, which is reflected in the indicators of technological effort compared to more developed countries. Thus, the sectors considered as high-tech by OECD[1] classification would present, in emerging countries, lower participation in R & D spending compared to the same sectors in developed countries. At the same time, it is observed in Brazil larger industrial weight and technological efforts in sectors that belong to the metal-mechanical industry (machinery, electrical and automotive equipment, basic metals, metal products) and to the basic chemistry (chemical, refined petroleum products, and rubber and plastics) (Furtado and Carvalho, 2005).

In this article, we intend, specifically: (1) to test whether measures of innovation and technology diffusion affect the patterns of sectoral mobility of Brazilian workers; (2) to evaluate the differences between the outcomes for skilled and unskilled workers and for those in high and low-tech sectors; and (3) to evaluate differences in the determinants of mobility between firms and sectors, in relation to the permanence in the same firm.

For the Brazilian case, we propose a multinomial logit model with random intercepts whose procedure is performed from the Generalized Linear Latent and Mixed Models (GLLAMM). The GLLAMM method has econometric advantages over the standard multinomial logit models, given the restrictive nature of the assumption of independence of irrelevant alternatives (iia) of the latter. Thus, this model appears more appropriate as it dispenses this hypothesis and, further, with the inclusion of random intercepts, allows the control of the sectoral unobservable heterogeneity.

[1] The OECD ranks high technological intensity sectors: aerospace, pharmaceutical, computer, electronics and telecommunications, and instruments; medium-high, electrical material, motor vehicles, chemical industries, excluding pharmaceuticals, and rail transportation equipment industry, and machinery and equipment; medium-low, shipbuilding, rubber and plastic products, coke, refined petroleum products and nuclear fuels, other non-metallic products, basic metal and metal products sectors; Low: other sectors and recycling, wood, pulp and paper, publishing and printing, food, beverages and tobacco, textiles and apparel, and leather and shoes.2 This study considers skilled individuals the ones with complete higher education whereas unskilled the ones that have at most incomplete higher education.

Empirically, a panel with individual data from the Annual Report on Social Information (RAIS – Migra) will be used for the years 2005–2008 and industry data extracted from the Brazilian Technological Innovation Survey (PINTEC), Annual Industrial Survey (PIA) and input–output matrices for the years 2000, 2003 and 2005, from the Brazilian Institute of Geography and Statistics (IBGE).

Following this introduction, the paper is organized into five sections. The second section presents a discussion of the literature on the subject, followed by the third section, which describes the methodology used. The section number four has the database and its sources. Finally, the results and main conclusions are presented in the fifth section.

2. Literature review

Based on the theoretical model of Griliches (1979), which relates inputs in the production of economically relevant knowledge to the outcome measures of a firm or industry (profit, productivity, innovation, etc.), it is noted that research and development (R & D) and the measures of human capital, skilled labor, and education are among the most important inputs of technological activity. Such inputs are acquired through direct investment or through the firm's acquisition or absorption of the external environment to the firm (spillovers), considering that the technical knowledge assumes properties of non-rivalry and exclusion only partial (Arrow, 1971).

One way to acquire knowledge of tacit nature, which is embodied in the individual, is through the mobility of qualified personnel (Feldman, 1999; Audretsch and Keilbach, 2005). Thus, the *learning-by-hiring* plays an important role in the technological learning process of a firm and in the extent of their technological frontiers (Song et al., 2003). The tacit nature of almost all valid knowledge (Song et al., 2003) causes the rate at which knowledge can spillover from one firm to another be dependent on the rate of mobility of persons owning high level of human capital (Feldman, 1999; Fischer and Varga, 2003; Cooper, 2001).

Furthermore, when individuals move between firms, they can apply the knowledge and skills they possess in a new context and thus transfer of the knowledge between firms efficiently (Song et al., 2003). For this transfer to be effective, the authors highlight three conditions: (1) the contracting firm should be less dependent on their past technological trajectory ("*path dependent*"); (2) the skilled worker hired must have a technological knowledge, arising from his experience, distant from the knowledge of the contractor; (3) the employee must work in an area that is not the specialty of the new firm.

Empirically, the relationship between labor mobility and innovation is confirmed by some studies. Cooper (2001) provides that labor mobility does not depend on the level of R & D invested in the firm, while Shankar and Ghosh (2005), on the other hand, found the opposite result. Moreover, in the case of France, both in terms of sectors and firms, higher levels of innovation are able to reverse the destruction of jobs and even create new jobs than those who do not innovate (Greenan and Guellec, 2000). For Estonia, this phenomenon would determine a positive relationship between mobility and innovation, since successful innovation would result in more hires (Masso et al., 2010).

In Italy, firms that invest more in R & D tend to have a more stable workforce. It is worth mentioning that in addition to the most innovative companies grow more lasting employer–employee relationships, they attract a larger share of those who change jobs (Pacelli et al., 1998). This is due to the fact that, when investment in R & D increases, the greater is the benefit of retaining the worker with experience in the area where it is applied R & D in the company (Shankar and Ghosh, 2005).

In the United States, there are evidence that, while knowledge spillovers increase the likelihood of this migration, there would be a negative relationship between innovation and interfirm worker mobility. Additionally, the negative relationship between investment in R & D and worker mobility is especially high in high-tech sectors, where the amount of investment in R & D leads to a shift of the technological frontier (Magnani, 2009).

As mobility and innovation are associated, it matters to assess the impact of innovation and technological diffusion on mobility. From there, we highlight some relations. First, it is argued that R & D can decrease interfirm worker mobility by increasing the value of the worker to the firm (Pacelli et al., 1998; Shankar and Ghosh, 2005). Second, the sustained idea is that innovation and diffusion have effect on mobility by affecting the generality of the knowledge and technology gap between sectors, influencing the skills acquired by workers in innovative sectors (Magnani, 2009).

To establish relationships between the effect of innovation and diffusion of knowledge in specific worker and the change in employment, Magnani (2009) identifies three assumptions: (1) in case the sectoral technological innovation is specific and covers the imperfect skill accumulation of the worker,[2] the sectoral innovation would adversely impact on intersectoral mobility of workers; (2) whether the specific technological innovation in the industry facilitates the assimilation and diffusion of new technologies developed in other sectors, the technological distance between i and j sector decreases and then leads to increased mobility; (3) the technology diffusion diminishes the technological distance between the sectors, making the ability of the worker more general, and therefore increases the probability of sectoral mobility.

Note that when changing jobs, workers seek similar occupations and industries to their origin (Parrado et al., 2007; Moen, 2005). Similarly, based on the specific ability of the individual, the adjustment of the worker within a sector should be less costly than between sectors (Elliott and Lindley, 2006). Workers who change jobs but remain in the same industry, get higher returns because of their experience (Neal, 1995).

In situations where the worker is more linked to the sector than to the company, his mobility will be higher and the flow of knowledge between firms will be intense (Dahl, 2004). In this case, workers will receive compensation for some skills that are neither general nor specific to particular company, but rather specific of an industry or line of work.

Contact with R & D activities allows a group of workers accumulate general human capital, in this case, one can interpret employment in intensive sector R & D as a type of training (Magnani, 2006) capable of increasing the marginal productivity of workers. To Mincer (1993), on-the-job training deepen specific knowledge of the worker, making him less likely to change jobs, so there would be a negative relationship between experience and mobility, i.e., the higher experience the lower the probability of changing jobs. Reinforcing this argument, Elliott and Lindley (2006) state that the most qualified individuals possess a specific skill to the industry making them less mobile.

Parrado et al. (2007), although they find that individuals with higher education levels tend to remain in the same occupation and industry recognize that education has positive and negative effects on the mobility of workers. While more educated workers have higher chances of early in the career find the desired job and would therefore be less likely to change jobs later, on the other hand, more skilled workers possess a larger stock of human capital and therefore would be able to develop a greater variety of activities (greater general knowledge) thus giving better opportunities to change their occupations. Thus, we observe that the empirical literature has no consensus on the relationship between educational level and likelihood of changing jobs.

For the United States, Magnani (2009) finds that innovation and technological diffusion have different effects on intersectoral labor mobility. The knowledge spillovers increase the likelihood of this migration, being this result more consistent for workers in low-tech sectors. Regarding innovation, the author highlights an ambiguous relationship between this variable and interfirm worker mobility, which may present a negative relationship, in the case of technological innovation be specific to the sector, and positive when this innovation technologically approaches two sectors. Thus, among those belonging to the low-tech sectors, innovation increases the probability of change of firm between sectors at the 2-digits, but, keeps a negative relationship with changes in firms across sectors and within the 3-digit sectors.

3. Empirical strategy

Based on the theoretical framework used by Magnani (2009) to characterize the influence of technological innovation and diffusion in intersectoral workers mobility, a representative firm h, belonging to the i-th sector, at time t, has a production function based on the number of skilled workers employed in terms of the internal labor market, L, and of a measure of current technological knowledge specific of the industrial sector $\omega_{\mathrm{i}}\omega_1$. Being K the capital stock, the function will be represented as $Y = F(L; K; \omega_i)Y = F(L; K; \omega_1)$. Thus, $V_{a_{hit}}$ will be the assessment made in the steady state for a skilled worker, of the value of employment in the h-th firm in industry i period t:

$$V_{a_{hit}} = \frac{W(L; K; \omega_i)}{rV_{\alpha_{hit}}} = \frac{W(L; K; \omega_i)}{r} \tag{1}$$

[2] Accumulation of the imperfect ability of worker refers to the fact that part of the skill of the worker not be fully absorbed by the firm who receives it. The ability of the worker is considered specific of the employment if the skill is only useful in the employment of origin, is not transferable if the employee changes jobs. It is considered transferable if it is usable in similar jobs for other workers and is considered general ability if can be used in any job.

where r is an market interest rate determined exogenously, and W (.), is the wages of the worker, determined by the firm's production function. The value being employed in another sector j must consider the cost of changing work places, which depends on the transferability of one's ability from one job to another. Therefore, it is assumed that the use of skill in another post is inversely proportional to the technological distance between the sectors of origin and destination, i and j respectively, formally represented by, $|\omega_j - \omega_i|$. Consequently, the value of the new job is defined as:

$$V_{a_{jit}} = \frac{W(L; K; \omega_i)}{r} - l(|\omega_j - \omega_i|) \tag{2}$$

being $l(|\omega_j - \omega_i|)$ the loss that the individual faces due to the fact that its human capital is only partially transferable when it changes from i to j. Thus, $l'(\cdot) > 0$. As a result, the impact of technological innovation on the mobility between sectors will depend on how the technology change in the current employment sector will affect the value given to jobs and the loss suffered because of the change of position.

For the construction of the econometric model, it is assumed that at time t a worker must choose to change firms between t and $t+1$, with the option of three types of mobility plus the option of stay on the job, as described by the dependent variable of the model, *mob*:

$$mob = \left\{ \begin{array}{l} 0 \text{ if the worker does not change firms} \\ 1 \text{ if changes firms but remains in the same3} - \text{digit sector} \\ 2 \text{ if changes firms and3} - \text{digit sector but remains in the same2} - \text{digit sector} \\ 3 \text{ if changes firms and2} - \text{digit sector} \end{array} \right\} \tag{3}$$

Therefore, the mobility of workers is represented as a categorical and discrete variable that may assume values mutually exclusive from zero to three. The explanatory variables (**x**) are the determinants of *mob* and represent characteristics of individuals, sectors and firms, being described in more details in the next section, and differentiated into the utility function ($U_{gt,J}$) expressed in Eq. (4). The worker will get a different level of well-being at each alternative, and choose the one that will maximize their utility.

As described by Magnani (2009), the utility associated with each type J of mobility, being J = 0, 1, 2, 3, from the individual g in period t will be:

$$U_{gt,J} = F(X_{gt}, X_{ht}, Ino_{it}, Dif_{it}) + \in_{gJt} \tag{4}$$

where i is the sector of origin of the worker, i.e., at time t; X_{gt} is the vector of individual feature and X_{ht} of the firms; Ino_{it} representing the variables characterizing the patterns of innovation in the sector; and Dif_{it} representing the variables characterizing the diffusion patterns. Thus, Eq. (4) represents the benefits earned by choosing each option J, given the costs of changing jobs.

As workers mobility is represented as a categorical and discrete variable and in view of the advantages of working with a regression for multiple results, the impact of individual characteristics and especially innovation and technological diffusion on the likelihood of changing firms is modeled by a multinomial logit model with random intercepts for panel data.

It is worth noting that this model, estimated by GLLAMM, which will be described in detail in Section 3.1, relaxes the assumption of independence of irrelevant alternatives (*iia*) and controls for sectoral unobserved heterogeneity from the inclusion of random intercepts. Thus, this becomes the most suitable model since, given the work's goals, we chose to work with categorical dependent variable. Additionally, the GLLAMM shows itself as a robust model because in addition to using the adaptive quadrature, which provides statistically more efficient estimates, considers in its construction the individual's choice from their utility function.

[3] The traditional multinomial logit model was also estimated, however, given the restrictive nature of iia hypothesis that is assumed and the robustness of the results of GLLAMM, the first model was not presented. The results of multinomial models are available upon request and in essence do not differ from those presented here, except for smaller values of the coefficients.

3.1. Multinomial Logit model with random intercepts[3]

The Generalized Linear Latent and Mixed Models (GLLAMM[4]) are a type of multilevel latent variable models for mixed responses, including ordered and unordered categorical responses. The model GLLAMM is estimated via maximum likelihood and uses adaptive quadrature to determine the log-likelihood obtaining more reliable results than other methods (Rabe-Hesketh et al., 2002).

The generalized linear mixed models include both fixed and random effects in the linear predictor and are used for grouped data, where observations within groups are not mutually independent, been applicable to panel data. One advantage of this application for this type of data is that the estimation is indifferent to whether the data are balanced or not (Rabe-Hesketh and Skrondal, 2008). The terminology of latent variables and mixed models implies that there are some unobserved variables that enter additively in the linear predictor. While the latent variables at the same level are mutually correlated, the ones at the different levels would be independent.

For the latent variables at level 1, we assume a discrete distribution. It is worth noting that in the present study, we work with two levels, the first individual and the second sectorial. Thus, the random intercept modeled by the hierarchical model, estimated via GLLAMM, corresponds to the second level, i.e., the sector, calculating the residual in level 2 (ξ_j). This is a specific error component of the sector, which remains constant between individuals. There is in the model a specific-error of individuals (level 1, $\in_{gj}$), which varies between the two levels, individuals and sectors. The two error components are mutually independent.

Being a the index representing the J possible categories of a polytomous response variable, the categories should be considered as alternatives, and the answer as a choice between alternatives, even in the event that the answer does not strictly represent the choice. Thus, we define the multinomial *logit* model adapted to GLLAMM by specifying the 'linear predictor' V_g^J, $J=0, 1, 2, 3$, so that the probability that the person g choose the response category J is expressed by Eq. (5).

$$Pr\,(J_g) = \frac{\exp\,(V_g^J)}{\sum_{J=0}^{3}\exp(V_g^J)} \tag{5}$$

The probability of the model can be derived by assuming that, associated with each alternative there is a 'utility' not observed U_g^j (latent variable) and that the alternative with the highest utility is selected. The utility of the individual g at time t, considering he chooses alternative J is given by:

$$U_{gt,J} = \beta_g' X_{gJt} + \in_{gJt} \tag{6}$$

X_{gJt} being the vector of observable factors specific of alternatives and $\in_{gJt}$ an *iid* error term independent from β_g'. The coefficient vector β_g' can be defined as the sum of an average effect (b) and the deviation of the individual relative to the average ($\beta_g' = b + \upsilon_g$). The latter ($\upsilon_g$) is thus a random component, which is assumed as part of the error term.

For identification, it is assumed that the error term cannot be correlated with the explanatory variables. Thus, the error component is random with zero mean, whose distribution among the g individuals and the J alternatives produces a structure of correlation between the set and subsets of alternatives involving mobility. Hence, the correlation between mobility options makes the assumption of IIA unnecessary.

From there, will be estimated a multinomial logit model with random intercepts by the equation:

$$\log\left(\frac{\pi_{gjr}}{\pi_{gj1}}\right) = \theta_r + x_{gj}'\beta_r + u_{gr,}r = 1, \ldots, R \tag{7}$$

where $\pi_{gjr} = P(mob_{gj} = r)$ are the probabilities of response, θ_r constant terms and the influence of the covariates are obtained from the components of $\beta_r = (\beta_{1r},\ldots,\beta_{pr})'$. The θ_r and β_r are considered fixed effects. One should remember that because it is a model of 2 levels there is a component of the level 1 error, specific of individuals ($\in_{gj}$), and a level 2 error (ζ_j). For the random intercepts ζ_j it is assumed a multivariate normal distribution with mean zero. In this way, for $u_g = u_{g1}, \ldots, u_{gR}$ we have $u_{gr} \sim N(0, \Sigma)$. The linear predictor, or the utility of the model, includes the specific individual covariate, such as the sex of the worker g of the sector j, x_{gj}, as well as the industry random intercepts.

[4] Model based on Rabe-Hesketh et al. (2002, 2004) and Rabe-Hesketh and Skrondal (2008).

The component specific-error of sector or random intercept combines the effects of the sectorial features omitted, namely, non-observed heterogeneity. Thus, being x_{gj} the observed variables, characteristics of individuals and sectors explaining the model, the assumptions of heterogeneity are: $E(\zeta_j|x_{gj}) = 0$; $E(\in_{gj}|x_{gj}, \zeta_j) = 0$; and hence $E(\in_{gj}|x_{gj}) = 0$. The random intercepts are therefore uncorrelated with the explanatory variables. The estimation via GLLAMM best forecast these random effects (unobserved heterogeneity of the sector) and the types of probability.

Rewriting the model, the probability of choosing J conditional to observed characteristics X_{gt} that vary between individuals and over time, and to the non-observed effects here written as α_g, constant in time, has the following form, being O the category of reference:

$$P(J|X_{gt}, \alpha_g) = \exp \frac{(X_{gt}\beta_J + \alpha_{gJ})}{\sum_{O=0}^{J} \exp(X_{gt}\beta_O + \alpha_{gO})} \tag{8}$$

As the probabilities of choice are a conditional α_g, it is necessary to integrate the distribution of the unobserved heterogeneity. Thus, the likelihood for the multinomial logit model with random intercepts is:

$$L = \prod_{g=1}^{N} \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{J=0}^{3} \left(\frac{\exp(X_{gt}\beta_J + \alpha_{gJ})}{\sum_{O=0}^{J} \exp(X_{gt}\beta_O + \alpha_{go})} \right)^{d_{gJt}} f(a)d\alpha \tag{9}$$

where $d_{gJt} = 1$ if the individual g choose the alternative J in period t, and 0 otherwise. During the estimation, for the selected base category, the coefficient vector (β_J) and the term representing the heterogeneity not observed in this category (α_{gO}) are taken as zero, to ensure the identification of the model. The non-observed effects obtained by the random intercepts are calculated for each individual (α_g).

The answer being a categorical variable (J = 0, 1, 2, 3) and O corresponding to the reference category (J = 0) in order to better characterize the relationships of the variables in the model, we calculated the relative risk ratio (*rrr*), which is the ratio between the probabilities of each category J and the reference O. It has been therefore $rrr = (p_J(x, \beta)/p_o(x, \beta)) = \exp(x\beta_J)$ where p_J(x,β) corresponds to the probability of the individual's response. Thus, the multinomial model calculates a series of *rrr*'s, which will compare each $J - 1$ category with the base class, J = 0.

4. Description of the database

In the present study, mobility is defined as the displacement of workers between firms in which they are employed, remaining or not in the same industrial sector, in the years 2005–2008. Thereafter, as the RAIS-Migra is a portrait of the worker on December 31 of each year, the variable of job mobility is constructed considering whether or not there was changing jobs a year over the previous. For example, if on December 31, 2005 the worker is linked to one CNPJ code, short for *Cadastro Nacional da Pessoa Jurídica* (Corporate Taxpayer Registry), and on December 31, 2006 to another CNPJ code, it is considered that this worker migrated from firm during the year 2006.

As one of the central goals of this article is to assess whether there are differences in the determinants of migration between firms and/or between manufacturing and extractive industries, we used the National Classification of Economic Activities (CNAE), with 2- and 3-digit aggregations, and the identification code of the firm (CNPJ), present in RAIS-Migra, for the construction of the dependent variable. Aiming to avoid reverse causality, the variables of innovation and technological diffusion were constructed so as to consider only the years prior to mobility. While the first are built cumulatively until the year 2005, the decision to change firm is identified from 2006 until 2008. It should be noted, however, that in order to avoid a sample selection bias, are present in sample both the workers who remain in the formal labor market in the industry every year and therefore have recorded their characteristics based on all years, as those who at some point leave the formal market or leave the industry.

The measures of innovation and technological diffusion were constructed from data of the Brazilian Technological Innovation Survey (PINTEC), from the Annual Industrial Survey (PIA) and the input–output matrices. For the individual characteristics and some of the control variables is used as a data source RAIS-Migra. This is a database derived from the Annual Report on Social Information (RAIS) administrative record and enables to tracking of the sectorial trajectories of workers over time (MTE, 2008). Although this base have the same disadvantages of other administrative records to be restricted to the formal sector of the economy, your choice is justified by the possibility of longitudinal monitoring of workers in extractive and manufacturing industries by tracking the Social Integration Program (PIS). Furthermore, the base allows to identify the firm from the CNPJ code, thus enabling verification of job changes.

From there, select the variables that indicate the following aspects of workers: educational level, age, gender, experience (tenure) and income in the last employment, in addition to variables indicating the sector where the individual works, with 2- and 3-digit aggregations. The effect of wages on mobility will be measured from the differential between the average wage in the occupation of origin and the salary of the individual observed before the change.

To ensure the independence of observations, a random sample of 20% of the universe of individuals belonging to the extractive and manufacturing industries present in RAIS-Migra was extracted. Subsequently, in order to avoid information that could bias the results, it was removed from the sample those individuals with inconsistent information,[5] obtaining a database composed of workers older than 18 years old, with greater than zero income in 2005 for each year, which compose altogether 1,468,308 observations from 2005 to 2008. From these, on average, 7.31% change jobs during the period analyzed. The panel was built unbalanced, keeping individuals who left the sample between years.

In innovation and technology diffusion literature, R & D expenditures play a decisive role. R & D expenditures are considered as flows and measured by the R & D intensity, i.e., R & D expenditures divided by the product of the firm. Therefore, the R & D intensity is considered a measure of technological effort of the industrial sector itself. However, as the process of technology diffusion depends on the absorption capacity of the technological knowledge that is produced outside the sector (Griliches, 1992), it is necessary to use the technical coefficients of production of input–output matrices to weigh the amount of R & D expenditures that a sector borrows from one another in the process of technological diffusion (Wolff, 2007). In this sense, we used the input–output matrices for the same years of the bases PINTEC and PIA, matching up the different sectoral aggregation of databases.

As innovation depends on the past trajectory of the R&D intensity (Song et al., 2003), both the measure of innovation and the diffusion consider the R & D intensity of the year you want to analyze it and the previous years. Thus, the measure of the last year will correspond to the sum of all the available years (2000, 2003 and 2005). It is also worth noting that will be considered as sectorial measure of production the value added of the industry, obtained from the PIA. Thus, the measure of innovation flow in sector i in period t is:

$$I\,\text{Flow}_{it} = \sum_{\tau} \left[\frac{\text{Expenditures in R\&D}_{i,\tau}}{\text{Product}_{i,\tau}} \right] \quad \text{with} \tau \leq t e \tau = 2000,\ 2003,\ 2005 \tag{10}$$

In order to check the technological diffusion among sectors, it is necessary to measure the indirect R&D, i.e., the amount of R & D imported by the sector i from the rest of the economy, which depends on the amount of R & D performed by the sectors. Therefore, from the flow method and based on the diffusion of embodied technology, this will be measured by means of indirect R & D taken from the transactions of intermediate and capital goods. Thus, the total indirect R & D will be:

$$\text{R\&D}\,indi_{it} = \text{R\&D}_{int_{it}} + \text{R\&D}_{cap_{it}} \tag{11}$$

being $\text{R\&D}_{int_{it}}$ the R & D embodied in intermediate goods flowing into the sector i in period t, and $\text{R\&D}_{cap_{it}}$ that embodied in capital goods.

Given that R & D expenditures are a proxy for technology and that is transported to other sectors through interindustry transactions, we use the inverse Leontief matrix for the construction of the variables that make up the measure of indirect R & D. Thus, since the intensity of the direct R & D (R_i) per unit of product (X_i) of sector i is $r_i = R_i/X_i$, the indirect R & D embodied in the final demand for sector j is obtained as follows:

$$\text{R\&D}_{int_{it}} = \sum_{i=1}^{n} r_i b_{ij} F_j \tag{12}$$

where F_j is the final demand for product from sector j and b_{ij} are the elements of the Leontief inverse matrix, or matrix B. Following the same principle, the R & D embodied in capital goods is calculated from the investment in the p-th

[5] It is considered an inconsistent observation one that has indicia of error filler, for example, are kept only those individuals who have the same rating gender every year. If there is any change in classification this observation is considered unreliable and is therefore removed from the sample.

Table 1
Description of variables used and expected signs in the regression.

	Variable	Description	Expected sign of the coefficient	Data source
Dependent variable	Mob	Interfirm and interindustry worker mobiliy. It can assume the values 0, 1, 2, 3	–	RAIS-Migra
	Wage differential	Difference between the average wage of the individual's occupation and the worker's wage	Positive	RAIS-Migra
	Age and age^2	Age and age squared	Negative/positive	RAIS-Migra
Explanatory variables	Tenure and tenure^2	Time of employment before moving ($t-1$) and the variable squared	Negative/positive	RAIS-Migra
	Female	Dummy of gender, takes 1 if female and 0 if male	Positive/negative	RAIS-Migra
	Skill	Dummy for college graduates	Positive/negative	RAIS-Migra
	Dummy of technology-intensive industry	Dummy, takes value 1 if it belongs to a technology intensive industry, and 0 otherwise	Positive	RAIS-Migra
	Dummy for engineer	Dummy, takes value 1 if the individual possessing bond in Engineering	Positive	RAIS-Migra
	Technological innovation (*P flow*)	Innovation flow	Negative/positive	PINTEC e PIA
	Technological Diffusion (*Dif flow*)	Diffusion flow	Positive	PINTEC, PIA e Input Output Matrix (IBGE)

Source: Prepared by the authors.

product realized by j sector which would be embodied into the input of capital $k(I_{kj}^{d})$ and of total inputs required by investment goods, $I_1, I_2, \ldots, I_n$,of industry j ($\sum_{k=1}^{n} b_{ik} I_{kj}^{d}$) of product of sector i:

$$\text{R\&D}_{cap_j} = \sum_{i=1}^{n} r_i \left(\sum_{k=1}^{n} b_{ik} I_{kj}^{d} \right) \tag{13}$$

In the present study, sector investment is measured from the amount invested in acquisitions, improvements and reductions in fixed assets, extracted from the PIA. Thus, if $k=1$, Eq. (13) becomes: $\text{R\&D}_{cap_j} = \sum_{i=1}^{n} r_i (b_{ij} I_j)$

From there, we get the measure of technological diffusion flow:

$$D\text{flow}_{it} = \sum_{\tau} \left[\frac{\text{R\&D}\, indi_{i\tau}}{\text{Product}_{i,\tau}} \right] \quad \text{with } \tau \le te\tau = 2000, 2003, 2005 \tag{14}$$

Given the previous definitions, Table 1 displays the variables used in the model, along with their expected signs and their sources. The variable wage should present a positive relationship with the dependent variable since the greater the difference between the average wage of the individual's occupation (proxy of expected wage prior to mobility) and the individual's own wage, the greater the incentive to job changes among firms and mainly sectors. This proxy for expected wage differential is constructed according to the methodology found in Mendes et al. (2012).

Furthermore, it is expected that the variable age shows a negative relationship with intersectoral mobility (Parrado et al., 2007), since their cost of job change would be greater. The same occurs for the case of the experience at the origin, measured by the time in which the employee remained in employment, which had before migrating, should show a negative relationship with mobility, consistent with the human capital models that point to a negative relationship between the mobility of workers and of workers' experience (Parrado et al., 2007).

The dummy variable gender can have positive or negative sign. On the one hand, the negative sign would be expected by the fact that women tend to change jobs less than men (Mendes et al., 2012; Parrado et al., 2007). On the other

Table 2
Average technological intensity across industries.

		Flow of innovation	Flow of diffusion
Non intensive sectors	Extractive Industry	0.010000	2.699265
	Food and Beverage	0.012875	1.896216
	Tobacco Products	0.027743	1.374.322
	Textiles Products	0.016901	1.844.418
	Clothing and accessories	0.015737	2.151.838
	Leather and Footwear	0.018751	1.607343
	Wood Products	0.008765	1.312113
	Pulp and Paper Products	0.015951	1.064427
	Publishing, Printing and Reproduction of Recorded Media	0.002910	0.431729
	Coke and Refined Petroleum Products	0.033323	0.738358
	Chemicals Products	0.047267	1.361.147
	Rubber and Plastic Products	0.028324	1.156.758
	Non-metallic Minerals Products	0.017460	0.502743
	Basic Metallurgy	0.018853	1.357295
	Metal Products	0.017775	1.517320
	Furniture and Miscellaneous Industries	0.024742	1.368.943
Intensive sectors	Machinery and Equipment	0.055255	1.369977
	Electrical Materials	0.135887	0.833471
	Computers and Electronics	0.092297	1.067633
	Manufacture and Assembly of Motor Vehicles	0.112328	1.447952
	Other Transport Equipment	0.255365	1.849682

Source: Authors' calculations based on data from PINTEC, PIA and IBGE.

hand, the fact of having children can make them leave and return to the labor market after a few years, making feasible the positive sign (Mincer, 1993).

For dummy-intensive industry in technology and engineering, proxy for the existence of technical knowledge in the firm, it is expected a positive sign. The more specific the knowledge less likely to go to another firm (Magnani, 2009), so given the general usefulness of this knowledge to the industry it is expected a positive sign.

Regarding the dummy of superior level, which may represent a proxy for the general knowledge, i.e., easy transfer (Magnani, 2009), it is expected a positive relationship with the interfirm and interindustry mobility of workers. However, as pointed out by some authors, this variable could introduce a negative relationship with mobility, given that these workers tend to invest in job training, which would increase their specific knowledge (Mincer, 1993). In the case of the subsamples of unskilled and/or employees of non-intensive sectors, the existence of specific knowledge, given the low qualification of these groups of workers, would increase the chances of absorption of this individual in another job, thus positively influencing the chances of mobility.

The assumption is that, as innovation increases, the technological gap between sectors also expands. Thus, the probability of changing jobs, and especially the sector decreases. Regarding diffusion, its increase would have a positive impact on mobility since it would decrease the specificity of worker's knowledge to increase the transferability of the skills acquired in the R & D activities, and reduce the technological gap between the sectors (Magnani, 2009).

Based on what was argued and Magnani (2009), we intend to test the following hypotheses:

(1) if the technological innovation is specific and includes accumulation of the imperfect ability of the worker, the sectoral innovation would adversely impact on interindustry mobility of workers;
(2) if the technological innovation specific of the sector facilitates the assimilation and diffusion of new technologies developed in other sectors, the technological distance between industry i and j decreases and then leads to increased mobility;
(3) the diffusion of technology decreases the distance between the sectors, contributes for the overall ability of the worker, and therefore, causes an increased probability of sector mobility.

Table 2 outlines an innovative profile of Brazilian industries displaying the averages of technological intensity between the two aggregate two digits sectors. It is observed that among the non-intensive in terms of flow of innovation, there is the manufacturing sector of chemicals. However, when considering all sectors, as might be expected, on average, those who innovate are more intensive in technology, especially the manufacturing sector of transportation equipment.

Since the manufacturing sector of transportation equipment includes companies such as Embraer, it is important to highlight their innovative importance in Brazil, emphasizing the international competitive advantage of this sector (Gonçalves and Simões, 2005). The flow of innovation indicates that spending on R & D in this sector corresponds to 25.54% of its value of production.

Thereafter, when evaluating the technology absorbed by the sector, measured by the diffusion flow, we indicate the extractive industry as the sector that receives most technology from other Brazilian industrial sectors, followed by the manufacture of clothing and accessories. In this case, it is worth noting that the average technology received from other sectors is higher among non-intensive than among intensive. When evaluating the technology-intensive sectors, the sector that receives more R & D embodied in intermediate and capital goods is the manufacturing of other transport equipment, with an index of 1.85. This means that R$ 1000 of industrial value-added correspond to R$ 184.97 R & D received from other sectors of intermediate and capital goods.

So while technology-intensive industries produce, on average, more technology, those who are not intensive are the ones that most absorb this technology produced externally. This fact is justified by those having a low level of production technology itself, requiring absorb this from other sectors. It is worth mentioning that the sections of vehicle assembly and the manufacture of other transport equipment absorb more technology than the average absorbed by non-intensive industries.

These technological specificities of the Brazilian sectors are described by Furtado and Carvalho (2005) that show structural differences in the patterns of technological effort of the Brazilian sectors in relation to a group of OECD countries. Besides the country perform less technological efforts in relation to the developed countries, these differences become more evident in the high technology industries compared to medium and low technology, following the OECD classification.

5. Results[6]

In order to expand the body of evidence about the influence of technological change on labor mobility, it was applied to the Brazilian case a model that could identify if technological innovation and diffusion affect the change of name and/or sector workers formal.

For the overall sample of formal workers in the Brazilian industry (Table 3), we observe that both innovation and diffusion affect the mobility propensity of the worker in relation to staying in their jobs. Technology affects the change of firm and sector by the workers by altering the technological gap between the sectors and the generality of the individual's knowledge.

It stands out that the increase in the flow of technological diffusion absorbed by the sector increases the probability of changing only jobs (intra-3 dig) and changing firms and 3-digit sectors (inter-3 dig). Such a phenomenon corroborates the third proposition of the study, according to which the diffusion reduces technological distance between industries by making the knowledge of the worker more general, which therefore increase the chances of mobility. The one-unit increase of the diffusion variable increases the chances of changing firms (intra-3 dig), firms and 3 digits sectors (inter-3 dig) by 89.10% ($rrr = 1.8910$) and 161.90% ($rrr = 2.6190$), respectively.

By observing the extent of innovation, it is noted a negative relationship with interindustry mobility (inter-3 dig and inter-2 dig). This phenomenon is linked to the fact that innovation generate specific knowledge, which negatively impact the intersectoral mobility, according to proposition (1). Thus, an increased flow of innovation negatively influences the change of firm and sector at 3-digit (inter-3 dig) and firm and sector at 2 digit (inter-2 dig), decreasing the probability of mobility in 99.35% and 53.82%, respectively. However, the innovation could also increase the probability of change of firm only (intra-3 dig) by a valorization of the acquired knowledge within the sector. In parallel, thus it increases the chances of change of firm only (intra-3 dig), which agrees with the proposition (2).

[6] Although the results presented are limited to the multinomial model with random intercepts, we tested the simple multinomial logit model. Thus, it is worth noting that although the direction of the relationship between the dependent variable and the explanatory remain the same between the models, the magnitude shown in multinonial is underestimated compared to random intercepts via GLLAMM. Thus, we demonstrate the importance of controlling for unobserved characteristics and the relaxation of the *iia* assumption. The results of the multinomial can be obtained from the authors request.

Table 3
Determinants of mobility of formal workers. 2006–2008 period.

Base category: not changed jobs	intra-3 dig		inter-3 dig		inter-2 dig	
	Coef	*rrr*	Coef	*rrr*	Coef	*rrr*
Technological diffusion	0.6371***	1.8910***	0.9628***	2.6190***	−0.0055	0.9945
	(0.0230)	(0.0435)	(0.0519)	(0.1360)	(0.0308)	(0.0306)
Technological innovation	6.3481***	5.7141***	−5.0338***	0.0065***	−0.7725***	0.4618***
	(0.1516)	(8.6618)	(0.5571)	(0.0036)	(0.2429)	(0.1122)
Expected wage	−0.0753***	0.9275***	0.1468***	1.1581***	0.5432***	1.7215***
	(0.0096)	(0.0089)	(0.0222)	(0.0257)	(0.0104)	(0.0179)
Dummy of technology-intensive sector	−0.6593***	0.5172***	0.4973***	1.6442***	0.4864***	1.6265***
	(00194)	(0.0100)	(0.0498)	(0.0819)	(0.0252)	(0.0410)
Dummy of skill	0.3770***	1.4578***	0.8536***	2.3482***	0.5387***	1.7137***
	(0.0156)	(0.0227)	(0.0366)	(0.0860)	(0.0227)	(0.0389)
Dummy for engineer	0.3208***	1.3782***	0.3324***	1.3943***	−0.0305	0.9700
	(0.0337)	(0.0465)	(0.0760)	(0.1060)	(0.0515)	(0.0499)
Dummy of female gender	−0.0585***	0.9431***	−0.5491***	0.5775***	−0.6228***	0.5365***
	(0.0113)	(0.0106)	(0.0334)	(0.0193)	(0.0194)	(0.0104)
Age	0.0222***	1.0224***	0.0167	10.169	−0.0170***	0.9832***
	(0.0034)	(0.0035)	(0.0105)	(0.0107)	(0.0062)	(0.0061)
Age^2	−0.0005***	0.9995***	−0.0005***	0.9995***	−0.0004***	0.9996***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tenure	−0.0094***	0.9906***	−0.0104***	0.9897***	−0.0165***	0.9836***
	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Tenure^2	0.0000***	1.0000***	0.0000***	1.0000***	0.0000***	1.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	−3.2073***	0.0405***	−4.9912***	0.0068***	−2.0733***	0.1258***
	(0.0666)	(0.0028)	(0.1991)	(0.0014)	(0.1135)	(0.0142)
Dummy – year				Yes		

Source: Authors' calculations based on data from the RAIS-Migra, PINTEC, PIA, IBGE and STATA 11.
Notes: (1) Standard deviation in parenthesis; *** significant at 1%; ** 5% * 10%.
(2) Intra-3 dig corresponds to changing of firm only; inter-3 dig, changing 3-digits sectors; and inter-2 dig, changing of sector at 2 digits.
(3) *rrr* is the relative risk ratio.

Proposition (2) states that the realization of technological innovation in the industry, in that it facilitates the assimilation and diffusion of new technologies developed in other sectors of the economy, reduces the technological gap between sectors i and j, increasing the possibility of intersectoral mobility of the workers (Magnani, 2009). This is more likely to occur in firms that are grouped in the same 3-digit sector than in more distant firms in terms of economic activity, i.e., classified in other sectors at 3 or even at 2-digit, because they share the same technological knowledge. In general, the results for the control variables had the expected signal being positive for $x1$, $x2$, and $x3$ and negative for, $y1$, $y2$ and $y3$.

Given the purpose of the study and the high statistical significance of the variables of skill (i.e., higher education) and technology-intensive sector variables in Table 2 above, the focus was set on the results for the subsamples presented below.

5.1. Subsamples of workers of Brazilian industry

From Table 4 it is possible to observe the relations between the variables of the models beyond the differences between the various sub-samples analyzed.[7] It is noteworthy that, in most cases, the variables have the expected sign, confirming the consistency of the model.

[7] The complete tables of the regressions can be provided by the authors upon request.

Table 4
Signs of the coefficients of the regressions on different subsamples of workers. Period: 2006–2008.

Variables	Subsamples	intra-3 dig	inter-3 dig	inter-2 dig
Technological Diffusion	Skilled	NS	+	+
	Non Skilled	+	+	-
	Intensive sectors	+	+	+
	Non intensive sectors	+	+	-
Technological Innovation	Skilled	+	-	-
	Unskilled	+	-	+
	Intensive sectors	+	-	-
	Non intensive sectors	-	-	+
Wage Differential	Skilled	-	-	+
	Unskilled	-	+	+
	Intensive sectors	+	+	+
	Non intensive sectors	-	+	+
Dummy of skill	Skilled	NI	NI	NI
	UnskilledUnskilled	NI	NI	NI
	Intensive sectors	+	+	+
	Non intensive sectors	+	+	+
Dummy of technology-intensive industry	Skilled	-	+	+
	Unskilled	-	+	+
	Intensive sectors	NI	NI	NI
	Non intensive sectors	NI	NI	NI
Age	Skilled	NS	-	-
	Unskilled	+	NS	-
	Intensive sectors	-	NS	+
	Non intensive sectors	+	NS	-
Tenure	Skilled	-	-	-
	Unskilled	-	-	-
	Intensive sectors	-	-	-
	Non intensive sectors	-	-	-
Dummy of female gender	Skilled	-	-	-
	Unskilled	-	-	-
	Intensive sectors	-	-	-
	Non intensive sectors	-	-	-

Source: Authors' calculations based on data from the RAIS-Migra, PINTEC, IBGE and STATA 11.
Notes: (1) NS = not significant and NI = variable not included in the regression.
(2) Blue signs represent that are consistent with the expected and red those who are not.

An increase in other sectors of technology absorbed by decreasing the technological gap between them and to increase the general knowledge workers would increase the chance of change of name for all replicates for almost all cases. Similar to the US results, as Magnani (2009).

In turn, an increased flow of innovation in the sector would increase the chances of changing only the firm (intra-3 dig) in the case of skilled workers, and unskilled-intensive sectors. In this case, innovation facilitates the assimilation of knowledge generated externally, which is in agreement with the proposition (2). Additionally, technological innovation has a positive impact on the change of firm and the two-digit industry in the case of unskilled workers and those of non-intensive industries by developing the capacity of technological learning that individual, allowing, in theory, that employee fits better a very different sector in comparison to the origin's sector.

In case of change of the 3-digit industry (inter-3 dig) and the 2-digit industry (inter-2 dig) skilled workers and intensive sectors, by increasing the specificity of the knowledge of individuals and promote the technological gap between sectors, negatively impacts innovation in this sector mobility, proposition (1). Similarly, among the unskilled, to change the 3-digit industry (inter-3 dig) and in the case of workers in non-intensive industries only to the change of firm and firm and sector at 3 digits. It is therefore highlight the similar behavior of skilled and intensive sectors and among unskilled and non-intensive sectors regarding the impact of technological innovation and diffusion on mobility.

In general, it can be concluded that, in most cases, technological diffusion positively affects the mobility of workers, while technological innovation seems to negatively affect the mobility to different sectors of origin of the employee. The exceptions are primarily in cases of change of firm and permanency in the same industry (intra-dig 3). In these cases, the knowledge acquired by the worker can be valued by firms in the same industry, which would explain the positive sign, especially in high-technology sectors and in the case of skilled labor.

When the difference between the expectation of the worker's salary in relation to its current earnings increases, the chances of change of firm only (intra-3 dig) decrease for skilled, unskilled and non-intensive sectors workers. In the case of skilled workers, it also occurs in mobility between sectors at 3 digits (inter-3 dig). As a negative wage gap means that the current wage of the employee is greater than your wage expectation, labor mobility, in this case, could be related to non-pecuniary reasons. Among these, stand out the accumulation of new skills and the desire to improve job satisfaction, responsibility or status (Fallick and Fleischman, 2004).

For unskilled and non-intensive sectors workers, in turn, an increase in the wage differential, increases the chances of change of firm and sector (inter-3 dig and inter-2 dig). It is noteworthy that for employees of intensive sectors, the monetary incentive is highly linked to the firm's decision to change, positively affecting all forms of mobility, consistent with the results reported by Jovanovic and Moffitt (1990).

Thus, we conclude that while non-pecuniary reasons may affect the decision to change only of the firm for skilled, unskilled and non-intensive sectors. Among workers in intensive sectors, any decision to change jobs is positively related to wage incentives, which can be explained by the value of the specific knowledge acquired on the job in theses sectors. In general, the observation in Table 3 shows that, in most cases, the expected positive coefficient is detected, confirming the cases of changes in industry of the general sample of Table 2 (columns inter-3 dig and inter-2 dig).

Regarding skills, the fact that the individual has university degree, compared to not owning, increases his chance of job change in all cases. This result is important because it shows that the mobility of these professionals can carry technological knowledge from one firm to another, given that the capacity for invention and R & D is largely associated with skilled workers employed in industrial firms. Thus, we emphasize that the more education, the more general is the knowledge of the individual, which increases their chances of changing jobs by increasing the chances of transfer of their tacit knowledge (Magnani, 2009).

As can be seen for skilled and unskilled workers, in Table 3, individuals who work in intensive sectors are less likely to move only of firm (intra-dig 3) and more likely to move to firms in other sectors, in relation to skilled and unskilled workers who work in non-intensive sectors. This result could be linked to the appreciation of the specialized worker, as evidenced by Shankar and Ghosh (2005). So by the appreciation of this specificity of knowledge, firms try to keep their workers so they do not move to other firms while trying to attract workers from other sectors that possess such knowledge.

Older age decreases the probability of changing sector of skilled workers (inter-3 dig and inter-2 dig) and mobility of workers only of firm from non-intensive sectors (intra-dig 3). While a higher age increases the probability of mobility only of firm, the older worker has less chance of changing industry, in the case of unskilled workers and the non-intensive sector. Regarding the age variable in the econometric exercises of different subsamples, it is not possible to establish clear link with respect to the sign of the coefficients found, which are divided into negative, positive and not significant.

Besides, greater tenure decreases the chances of change of employment in all cases. This would be consistent with models of human capital that point to a negative relationship between the mobility of workers and the tenure of the worker (Parrado et al., 2007). Similarly, the fact that the worker is female reduces the probability of changing jobs compared to males, similar result that appear in other studies about Brazil that use the same type of micro-data from the RAIS-Migra (Mendes et al., 2012).

6. Conclusion

Little is known about the effects of technical change on the mobility of workers, thus, this study empirically found that the flows of innovation and technological diffusion have influence on labor mobility. In general terms, while the former has a relation with the mobility of labor, innovation has different effects according to the group of workers analyzed. We highlight the different aspects when analyzing the skilled and unskilled workers and those in intensive and non-intensive sectors. We observe similar behavior between skilled and intensive sectors and also among the unskilled and non-intensive sectors, as to the impact of technological innovation and diffusion on mobility.

Comparing the results obtained for samples of skilled and unskilled individuals, it is observed that the flow of innovation has a positive relationship with the mobility of firm only (intra-3 dig) and affects negatively the mobility between sectors at 3 digits, for both cases. Among individuals belonging to intensive sectors, it is emphasized that innovation presents positive influence merely in case of change of firm only, being the intersectoral mobility adversely affected. Among workers in non-intensive sectors, the flow of innovation would increase the chances of sectoral mobility.

An offshoot of this future work is to consider regional aspects of labor mobility in order to evaluate the possibilities of diffusion of technological knowledge between regions, to understand one of the factors that can reduce regional inequalities. Another possible development is to change the ways of measuring diffusion and innovation, which could take into account measures of stock of technological knowledge accumulated by sectors.

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