Turnover, Learning by Doing and the Dynamics of Productivity in Brazil

Leandro Pereira da Rocha
Instituto de Economia - Universidade Federal do Rio de Janeiro

Valéria Lúcia Pero
Instituto de Economia - Universidade Federal do Rio de Janeiro

Carlos Henrique Corseuil
Instituto de Pesquisa Econômica Aplicada

Abstract

This article analyses the effect that labor turnover had on the productivity of Brazilian manufacturing firms between 1996 and 2013. We based our analysis in a theory of learning by doing, where turnover harm productivity by restricting efficiency gains achieved by workers via the accumulation of learning that results from the act of producing in the same firm. We estimate a learning measurement that takes into account the loss of human capital—resulting from turnover—and its effect on total factor productivity (TFP). Our learning measurement is shown to be robust and has a consistent positive relationship with three different estimates of TFP.

Keywords: labor market, turnover, learning by doing, learning, productivity.

Resumo

Neste trabalho estudamos o efeito da alta rotatividade no mercado de trabalho sobre a produtividade da indústria brasileira entre os anos de 1996 e 2013. Utilizaremos a literatura de *learning by doing*, que parte da hipótese de que ganhos de produtividade intra-firma podem se dar através de ganhos de eficiência alcançados através do acúmulo de aprendizado decorrente do próprio ato de produzir. Estimaremos uma medida de aprendizado que capte a perda de capital humano, decorrente da rotatividade, e seu efeito sobre a produtividade total dos fatores (PTF). Nossa medida de aprendizado mostrou-se robusta e apresentou uma consistente relação positiva com três diferentes estimativas da PTF.

Palavras Chave: Mercado de Trabalho, Rotatividade, Learning by Doing, Aprendizado, Produtividade.

JEL classification: D24, J24, O47

Área da ANPEC: Área 13 – Economia do Trabalho

Introduction

Historically, a predominant feature in the Brazilian job market has been its high turnover rate. In international comparisons, it is often concluded that Brazil has one of the highest rates of job turnover among countries with available measures (Gonzaga, 2003).

The first decade of the 2000s was marked by the sound performance of the economy and the job market, with an increase in the formalization of employment and a decreasing trend for unemployment rates (Corseuil and Foguel, 2011). In addition the increase in labor force educational level that took place in the 90's continued during the 2000's. Despite all these improvements in labor market, there was an increase in the turnover rate in this period and stagnation of labor productivity (IPEA, 2012).

Accordingly, the high rate of job turnover has been indicated as a cap to the growth of labour productivity in Brazil (Gonzaga, 2014; Corseuil et al., 2013). To some extent, the reason is that high turnover is associated with low levels of commitment and investment in professional training, both by workers and by firms, with consequences for labor productivity.

The main objective of this paper is to understand the consequences that high turnover has for the economy through its effects on labor productivity. To that end, we estimate a learning measurement that captures the loss of human capital resulting from turnover.

The international literature indicates several determinants for productivity growth, and among them is the effect of learning. According to the concept of "learning by doing", the more a worker produces, the more he accumulates experience, thus becoming more efficient in performing his task (Wright, 1936; Arrow, 1962). However, as observed by Argote et al. (1990), learning is not accumulated constantly and equally among firms—there is the possibility that knowledge will suffer a type of "depreciation". Chiang (2004) adopts the idea of learning depreciation; however, instead of estimating a depreciation rate—something that the author considered to be abstract—a more explicit measure is used: turnover. The basic idea is that the productivity of a firm is a function of the learning acquired over time by all of its employees. Therefore, firms with high labor turnover will have more difficulty in accumulating knowledge and, consequently, in increasing their productivity.

Due to the importance of labor productivity growth for economic development, the idea is to contribute to this topic by analyzing the relationship between the learning acquired in production and labor productivity at micro level.

1. Turnover, human capital, and learning by doing

One of the consequences of the labor turnover is the loss of the experience accumulated by firms. Basically, this occurs because the individuals participation in the productive process hold the experience and, when they leave their job, the knowledge accumulated is lost. In particular, the firm will lose knowledge if the worker who left the firm has accumulated specific capital during his time working in the job (Becker, 1993).

Thompson (2007) cites three explanations for understanding the occurrence of knowledge depreciation in the productive process: (i) when a technological change occurs in production, past experience becomes irrelevant; (ii) organizations often fail in the process of recalling experiences because they have imperfect or inadequate memory systems; and (iii) tacit knowledge passed to employees is lost when they leave the job. Considering these explanations, only the third can be subjected to direct testing.

1.1. Turnover and human capital

The Theory of Human Capital (Schultz, 1961; Becker, 1962; Becker, 1993) shows that productivity depends on the qualification of the labor force, which are largely a function of an individual's education level. In this function, another fundamental variable for explaining productivity is the specific human capital accumulated through training in the work environment. Therefore, the knowledge and skills of an individual, innate or acquired, determine his productivity.

Schoolling enables the acquisition of general knowledge that will be complemented by the specific knowledge acquired by the individual throughout his active life. This specific knowledge can, in turn, be acquired through on the job experience and training or through specialization courses.

Investment in human capital can be undertaken by the firm itself; however, it tends to be specific training. , In this sense, the on the job training generates a firm specific skill, minimizing the transference of skills and the possibility that those who have been trained will leave the firm. If turnover is high, then investments in specific human capital becomes unviable. After all, firm's investiments on training tend to be more feasible when employee remains longer in the job.

In the traditional model of human capital, wages reflect the worker's productivity, which depends on the stock of human capital. One of the hypotheses is that time at work is also an investment in human capital, in which skills can be acquired as a by-product of the work (learning by doing) or through specific training during working hours (on-the-job training) (Heckman, Lochner, and Cossa, 2002).

Several studies have indicated that productivity will be a function of the learning acquired on the job over time. Guthrie (2001) examine the relationship between employee retention and corporate productivity. The results of this author's study indicate a positive association between the firms that retain their employees for longer periods of time and their productivities, particularly for firms that have a higher commitement level of production's workers. Therefore, the basic idea is that firms with high labor turnover will face more difficulties to increase their productivity.

In a review of the Mincerian approach, Heckman et al. (2006) draw attention to a more general model formulated by Mincer (1974), in which returns on experience may be different among individuals. One method of characterizing this heterogeneity is to observe the average return for experience in different groups. The authors show that the return on experience occurs heterogeneously between different groups of schooling.

Gathmann and Schonberg (2010) use information on occupational tasks from the German data source BIBB to create a unidimensional measurement of domain over tasks. Accordingly, they propose the concept of task-specific human capital and include this measurement in the wage equation. Their conclusion is that more than 50% of wage growth is explained by this measurement and, furthermore, it increases with occupational stability or imminent occupational movements.

Yamaguchi (2012) estimates a structural model of heterogeneous human capital using a Kalman filter. The results from this author's estimation indicate that workers employed in occupations with more complex tasks have faster growth in skill. Additionally, the results also show that cognitive skills play a central role in wage growth.

1.2. Learning by Doing

Arrow (1962) assumes that the accumulation of knowledge, or human capital, arises from learning by doing. The argument used is that learning is the product of practical experience, which is acquired during the production process, in which the worker will be exposed to challenges and the possibility of trying to solve problems. Thus, it is possible to develop the production process through the production process itself, and therefore, the increase in productivity of the economy may be derived from the amount of experience acquired in the elaboration of a particular product or process.

The process known in the literature as "learning by doing" occurs through the investment that each firm makes in its productive process. This formulation is based on the hypothesis that costs are a decreasing function of accumulated production. The fundamentals of this formulation have been confirmed in the international literature by empirical studies over the years.

Traditional models of learning by doing considered the accumulation of experience that generates learning is given by the accumulation of production (or investment) over time. Preston and Keachie (1964) find that both the costs of each product unit and the costs of labor decreases with the accumulation of production. Rapping (1965) shows that the observed increase in production over time (during a process of production accumulation) is not simply due to the increase in the insertion of labor and/or capital, the increase in the exploitation of economies of scale, or the mere passage of time. The author finds convincing evidences of the occurrence of productivity gains through learning at the organizational level.

Therefore, according to the traditional models, if, given the same technological conditions, there are no differences in the initial productivity of two firms and, over time, the productivity of these two firms remains the same, then it can be assumed that the production decisions (and/or investment) were identical. Thus, productivity differences would occur because the firms have different production (or investment) decisions or simply because some firms are older or newer than others. However, these models do not seem to be very consistent with reality because they do not consider the possibility of losses in the stock of knowledge.

Unlike the "traditional" models, the newer models have admitted the possibility that experience gains will not occur perpetually. The new models introduce the hypothesis that there is a certain rate of "depreciation" or "forgetting" of the stock of knowledge. Argote et al. (1990) find results indicating that the learning acquired through production depreciates rapidly, which therefore shows that the results obtained through the traditional models had been overestimated.

Some important studies have been published in recent years emphasizing the experience acquired over productivity gains in various sectors of activity (Benkard, 2000; Chiang, 2004; Thompson, 2007; Brachet and David, 2011; Levitt, List, and Syverson, 2012).

Benkard (2000) analyzes commercial aircraft production, with an emphasis on production dynamics in the 1970s and 1980s. The author uses a learning by doing model and finds evidence that learning is determined stochastically rather than deterministically. Therefore, he notes that during the execution process, the worker can internalize or not the knowledge, and can alsoforget a portion of the acquired knowledge. Thus, he introduces the hypothesis of organizational "forgetting", in which the accumulated experience of firms depreciates over time.

Analyzing data from the manufacturing sector of the United States, Chiang (2004) shows that learning is affected not only by past production but also by the worker turnover rate within firms. The author uses the hypothesis that firms with high turnover rates have greater difficulty in retaining learning by doing. Based on this assumption, the author estimates that firms with a history of low turnover "learn" faster than those with a history of high turnover, given the same amounts of production.

New estimates for rates of organizational "forgetting" are provided by Thompson (2007). Using data from shipbuilding in the United States during World War II, the author achieves more modest results than the literature indicate for the rates of forgetting. In cases in which learning was limited, this effect might not even have existed. By including in his model the effects of the turnover rate of firms, the author also diverges from the literature by not finding significant results concerning the effects of turnover on learning and, consequently, on productivity.

In line with Chiang (2004), Brachet and David (2011) find robust estimates that the high turnover of ambulance companies in Michigan (USA) increases the levels of organizational "forgetting". The authors test two effects: (1) the turnover rate and (2) the possible skill losses of workers who remain in the job. The results show that the effects of the former are twice the magnitude of the latter.

2. Databases and methodology

2.1. Databases

Two databases are used in this study. The first is the Annual Social Information Report (Relação Anual de Informações Sociais - RAIS) of the Ministry of Labor and Employment (Ministério do Trabalho e Emprego - MTE), and the second is the Annual Industrial Survey (Pesquisa Industrial Anual - PIA) of the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística - IBGE).

The RAIS is an administrative record requested from legal entities and other formalized employers, with information about the characteristics of the employees and the job in the base year. As this base is a census of formal employees and employers, it represents enormous potential for analyzing the formal job market at the national level. The data available enable a series of analytical cross-sections to be made, according to aspects such as: geographical region, economic sector, occupation, gender, level of schooling, and age group, among others. The data refer to information on jobs, establishments, turnover, and remuneration.

At its most disaggregated level, the RAIS provides data for each worker. At this level, we obtain data related to the human capital of workers, for example: age, level of education, and remuneration. The data are then aggregated by firms to obtain the indicators related to the characteristics of the firms. At this level, only firms that operate in the industrial sector will be filtered to continue in the database to be compatible with the IBGE's Annual Industrial Survey (PIA).

The PIA identifies the basic structural characteristics of the business sector of the industrial activity at the national level, and it is conducted on an annual basis. The survey presents data on employees, costs and expenses, revenue, production value, and the value of the industrial transformation, among others. The industrial classification is performed based on version 2.0[1] of the National Classification of Economic Activities (Classificação Nacional de Atividades Econômicas - CNAE).

The two databases, aggregated at the firm level, are interlinked by means of a unique identifier. The key variable that makes it possible to link the two databases is the National Registry of Legal Entities (Cadastro Nacional de Pessoa Jurídica - CNPJ). After they are linked, we obtain an unbalanced panel of firms for the 1996-2013 period. It is worth noting that the merging of the databases was performed within a confidentiality room of the IBGE and that all rules of statistical confidentiality were respected.

The monetary variable of the PIA used to calculate productivity (added value) was deflated by the Global Supply Wholesale Price Index (Índice de Preços por Atacado-Oferta Global - IPA-OG) of the Getulio Vargas Foundation (Fundação Getulio Vargas - FGV), the three-digit CNAE. When doing so was not possible, the two-digit deflator was applied. The wage variable of the RAIS was deflated using the Extended Consumer Price Index (Índice de Preços ao Consumidor Amplo - IPCA), calculated by the IBGE.

2.2. Methodology

2.2.1. Definition and measurement of turnover

The concept of labor turnover is often associated to the substitution of one worker by another in the same job., The empirical counterpart of this concept is usually measured using the following formula:

$$turnover\ rate\ (tr) = \frac{min\ (hirings; separations)}{jobs} \text{ x } 100$$

[1]Version 1.0 of the CNAE was released from 1996 to 2007. The changeover to version 2.0 occurred after 2007. This changeover required a conversion of the sectorial classification of CNAE 1.0 to CNAE 2.0 in the years prior to 2007.

In fact even a separation not driven by worker substitution will harm the learning by doing process that motivates our analysis. Therefore, an additional turnover measurement is used, in which we consider any separation. This is calculated as follows:

$$separation\ rate\ (td) = \frac{separations}{jobs} \text{ x } 100$$

The separation rate, similar to the turnover rate, is calculated at the firm level, and afterwards, the two rates will be aggregated.

TABLE 1. Turnover rate and separation rate, 1996-2013

Year	Turnover rate	Separation rate
1996	42.9	78.4
1997	44.5	87.7
1998	37.6	85.3
1999	37.7	119.9
2000	44,0	106.8
2001	42.8	90.7
2002	38.2	75.4
2003	38.1	79.8
2004	40.1	71,0
2005	41.8	83.7
2006	41.7	78.7
2007	45.7	90.3
2008	64.1	116.9
2009	43.9	84.6
2010	52,0	95.7
2011	53.7	92.6
2012	48.1	66.6
2013	49.5	67.9

Source: RAIS (MTE)

Table 1 shows the evolution, between 1996 and 2013, of the two rates calculated for the sample analyzed in this study. The turnover rate reached 49.5% in 2013 and peaked in 2008 at 64.1%. The separation rate was 67.9% in 2013 and had its peak in 1999, when it reached 119.9%. It can be observed that the turnover rate based on the concept of worker substitution induces a smoother time evolution.

The trajectory of the turnover rate in the recent period shows that it remained at levels between 37 and 45% between 1996 and 2007 and that, after reaching its peak in 2008 and decreasing slightly in 2009 due to the effects of the international crisis, From 2010 onward, the turnover rate remained at a higher levels, between 48 and 52%.

The separation rate has a greater variance in its evolution and higher levels. In years of economic crisis, as in 2008 and 1999-2000, the rate surpassed 100%.

2.2.2. Learning measurement

In traditional learning models, the empirical counterpart of the contribution of experience accumulation to productivity growth is simply defined as accumulated past production. In more recent models, the possibility that this learning may suffer from "depreciation" or "forgetting" is incorporated. The departure point for these models is the following definition of learning, based on the accumulation of experience:

$$E_{it} = \delta_t(E_{it-1} + q_{it-1}) \quad (3)$$

where E_{it} is the experience accumulated by the firm in production until the beginning of year t, and E_{it-1} is the experience accumulated until the beginning of the immediately preceding year. The term q_{it-1} is the production of the firm in *t-1* (also measured in GPV). The "depreciation" of the learning is represented by δ_t, which is bounded between 0 and 1. Note that we allow for time variation in the depreciation, which contrasts with a standard assumption of fixed rate of depreciation in models of (physical) capital accumulation.

In this article, a direct measurement is used as a proxy for the time varying rate of depreciation—as noted above, this measurement is the turnover rate (*tr*). Thus, we follow Chiang (2004) in using the following measure for experience accumulation:

$$E_{it} = (1 - tr_{it-1})(E_{it-1} + q_{it-1}) \quad (4)$$

Ii one extreme case, if in a period *t* a firm decides to replace all of its employees, then its turnover rate will be equal to 1. In this case, all of its specific human capital will be lost; that is, its learning measurement will be equal to zero. However, if the firm maintains the same employees, then its turnover rate will equal zero, and therefore, there will be no learning losses due to "depreciation".

Additionally, in an attempt to capture the effect that any departure of workers has on firms, we use a learning measurement that uses the separation rate (*sr*) instead of the turnover rate for depreciation:

$$E_{it} = (1 - td_{it-1})(E_{it-1} + q_{it-1}) \quad (5)$$

The data on separations, hirings, and jobs, in addition to the calculation of the turnover rate and the separation rate, are obtained from RAIS data. After being aggregated at the firm level, the RAIS data are linked to the PIA data, also at the firm level, and accordingly, we obtain the data on production, , so that we can estimate the final model.

2.2.3. General human capital indicator

The learning measurement described in this work can be defined succinctly as the sum of the human capital acquired in the course of the firm's production process. As noted above, the human capital of the worker can be divided into general human capital and specific human capital. The first type is that acquired by the worker throughout his life (education, life experience, etc.), whereas the second type is that acquired within the firm.

The objective of this work is to observe how variations in learning affect the productivity level of firms. To that end, one challenge is to be able to isolate specific human capital from general human capital. Abowd, Lengermann, and McKinney (2005) and Chiang (2004) estimate human capital via the following model:

$$w_{ait} = x_{ait}\beta + \varphi_i + \varepsilon_{ait} \quad (1)$$

The dependent variable is the log of the wage of individual *a* working in firm *i* in year *t*. The component x_{ait} represents a vector of the individual observed characteristics, such as age (measured in years), and schooling level (dummies). The next component, φ_i, represents the fixed effect of the firm, and the last term is the residual of the model.

The employee's wage rate is given by the sum of the market value of his personal characteristics and the employer's specific remuneration policies. Some personal characteristics, such as experience in the job market, evolve over time, whereas others, such as education and some unobserved component (such as "ability"), remain constant. Stochastic variations in these personal effects, in addition to the effects of firms, are ignored.

The measurement of general human capital, which will call h, is formed by the combination of the observable component of the individuals using the estimated parameters from equation 1 ($\hat{\beta}$). Thus, we have the following:

$$h_{ait} = x_{ait}\hat{\beta} \tag{2}$$

We use two measurements of general human capital. The difference between them is in the specification of the education dummies. The first is aggregated into the following categories: Incomplete Elementary Education, Incomplete secondary education, and Completed secondary education. The alternative measurement is aggregated into: Incomplete Elementary Education, Some tertiary Education, and Completed tertiary education Education. The second classification is more affected by movements in tertiary education.

We use the RAIS data at their most disaggregated level to obtain information on workers' wages, age, and educational level. The estimates are obtained at the worker level, and these are subsequently aggregated at the firm level to obtain the results from the main model.

2.2.4. Total Factor Productivity

For the productivity measurement, we follow the approaches conducted by Messa (2014)—who calculates the Total Factor Productivity (TFP) using econometric methods applied to Brazilian manufacturing plant level data. Starting from a Cobb-Douglas production function, such that the product (Y) of firm i at time t is a result of the combination of the capital (K) and labor (L) factors due to technology (A), we have the following:

$$Y_t = A_{it}K_{it}^{\beta_K}L_{it}^{\beta_L}$$

The TFP calculation can be performed using different methodologies. The following three estimates that are commonly utilized in the literature are used: (i) ordinary least squares, (ii) the Olley-Pakes method, and (iii) the Levinsohn-Petrin method. The description below closely follows the corresponding topics in Messa (2014). The TFP estimates are calculated based on the PIA data.

i) Ordinary Least Squares

The simplest method of obtaining a measurement of productivity is to run a simple regression via ordinary least squares (OLS). The objective of this method is to estimate the parameters so that the deviations (error vector) between the observed and estimated values are minimal. Extracting the logarithm from the production function described above, we have the following:

$$y_{it} = \beta_0 + \beta_K k_{it} + \beta_l l_{it} + \varepsilon_{it} \tag{6}$$

The lowercase letters represent the natural logarithm of the respective variables, the β's represent the parameters to be estimated, and ε is the error term. However, despite the simplicity of using this method, it may result in problems that would violate certain assumptions of the OLS method and would yield biased estimators.

When estimating the production function, the error term (the deviations in relation to the mean) of the equation, which is being associated with the TFP, may also have some relationship with the explanatory variables. This problem, known as simultaneity, harms the basic assumptions of the OLS method. To overcome these endogeneity problems of the OLS method, the literature presents some alternatives, for example, the methods of Olley-Pakes (1996) and Levinsohn-Petrin (2003).

ii) Olley-Pakes Method

The measurement proposed by Olley and Pakes (1996) estimates a production function consistently, considering the problem of endogeneity. The authors use an observable variable as a proxy for productivity. To be a good proxy, the chosen variable must be correlated as much as possible with productivity. The Olley-Pakes method uses the investment flow variable of firms as a proxy.

Starting from (6), we can divide the residual into two parts: $\varepsilon_{it} = \omega_{it} + \vartheta_{it}$, in which ω is composed of unobservable characteristics that influence the decision of the firms and ϑ is the idiosyncratic shock. From the results found in Olley and Pakes (1996), the authors assume that ω is a stochastically increasing time sequence and that the investment flow can be written as i = $f\,(\omega_{it}, k_{it})$, in which f is a monotonic function in ω. Inverting f, we have $\omega_{it} = g(i_{it}, k_{it})$. Thus, (6) can be rewritten as follows:

$$y_{it} = \beta_l l_{it} + \varphi(i_{it}, k_{it}) + \vartheta_{it} \tag{7}$$

$$\text{where:} \varphi(i_{it}, k_{it}) = \beta_k k_{it} + g(i_{it} + k_{it})$$

and φ can be estimated by a third-order polynomial. Thus, from (7), we obtain the estimate $\widehat{\beta_l}$. To obtain the estimate of β_k, we rely on innovation in productivity, based on the last period expectation: $\zeta = \omega_{it} - E[\omega_{it}|\omega_{it-1}]$. Thus, we rewrite (7) as follows:

$$y_{it} - \widehat{\beta_l} l_{it} = \beta_k k_{it} + h(\widehat{\varphi_{it-1}} - \beta_k k_{it}) + \zeta_{it} + \vartheta_{it} \tag{8}$$

From (8), we obtain a consistent estimate for β_k.

iii) Levinsohn-Petrin Method

To overcome the problem resulting from the investment flow variable used in the Olley-Pakes method, Levinsohn and Petrin (2003) propose another variable to be used as a proxy for productivity. For these authors, expenditures with intermediate inputs would be more efficient for capturing the dynamics of productivity.

The first stage of the Levinsohn-Petrin method is analogous to that of Olley and Pakes (1996), described in (7). The only difference is the substitution of the variable *i*—which represents the investment flows—with the variable *m*, which represents the intermediate costs, such that $m_{it} = f(m_{it}, k_{it})$. Thus, we obtain the estimate of $\widehat{\beta_l}$.

For the second stage, any candidate β_k^* is used, with the objective of computing a predicted value for $\omega_t$for all periods *t*:

$$\widehat{\omega_{it}} = y_{it} - \beta_k^* k_{it} - \hat{\beta}_l l_{it} \tag{9}$$

Using the values obtained in (9), a consistent (non-parametric) approximation for $E[\omega_{it}|\omega_{it-1}]$ is given through the predicted value of the regression.

$$\widehat{\omega_t} = \gamma_0 + \gamma_1 \omega_{t-1} + \gamma_2 \omega_{t-1}^2 + \gamma_3 \omega_{t-1}^3 + \varepsilon_t \tag{10}$$

After obtaining $\widehat{\beta_l}$, β_k^*, and $E[\widehat{\omega_{it}|\omega_{it-1}}]$, we can compute the residuals of the production function so that we can then obtain the estimate for $\widehat{\beta_k}$. This is obtained through the solution to the following problem:

$$\min_{\beta_k^*} \sum_i \sum_t (y_{it} - \beta_k^* k_{it} - \widehat{\beta}_l l_{it} - E[\widehat{\omega_{it}|\omega_{it-1}}])^2 \tag{11}$$

2.2.5. Estimating the effects of learning on TFP

The aim here is to find the effects of the turnover rate on labor productivity through learning. Therefore, to find the desired effect, according to Chiang (2004), the following equation is estimated:

$$prod_{ijt} = \gamma_0 + \gamma_j + \gamma_v v_i + \gamma_t t + \gamma_h h_{it} + \gamma_e e_{it} + u_{ijt} \tag{12}$$

$prod_{ijt}$ is the measure of total factor productivity (TFP) of firm i in sector j at time t; γ_j is the specific effect of the sector of activity defined by the National Classification of Economic Activities; v_i is the timing of entry of firms; t is an annual dummy introduced to capture the technological progress of the entire industry; h_{it} is the measure of human capital; e_{it} is the logarithm of the learning measure, $e_{it} = \log(E_{it})$. Lastly u_{ijt} denotes the error term.

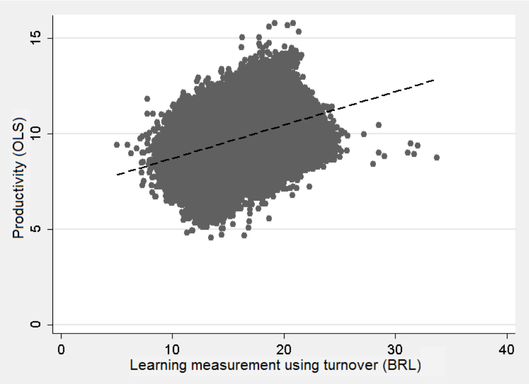
3. Results

In this section, the results from the models discussed in the methodological section are presented. We will highlight the effects that turnover has on productivity through learning. The graphs presented in this section seek to reinforce the relationship between the degree of learning and the level of productivity of firms. To that end, three measures of TFP are presented, as described in section 3.2.4.

3.1. Relationship between learning and productivity

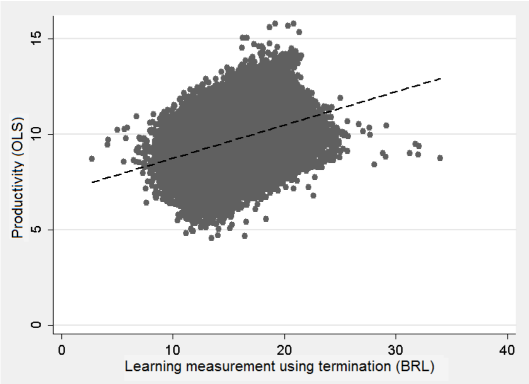
Graphs 1-4 are plotted pooling information from all firms in the sample. In Graphs 1 and 2, productivity is estimated by OLS while learning is measured using depreciation based on turnover rate in graph 1 and separation rate in graph 2. In both graphs, there is a lot of dispersion between firms, but the relationship between learning and TFP shows a clear positive trend. Both learning measurements show very similar correlation with TFP. Therefore, the remaining graphs will be shown only the learning measurement that uses the turnover rate as depreciation.

GRAPH 1. Mean for 1996-2013, all firms



Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 2. Mean for 1996-2013, all firms

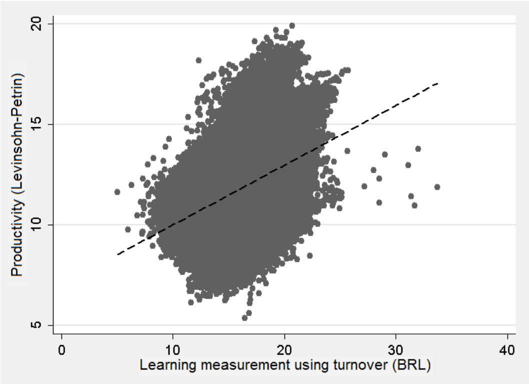


Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 3. Mean for 1996-2013, all firms

Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 4. Mean for 1996-2013, all firms

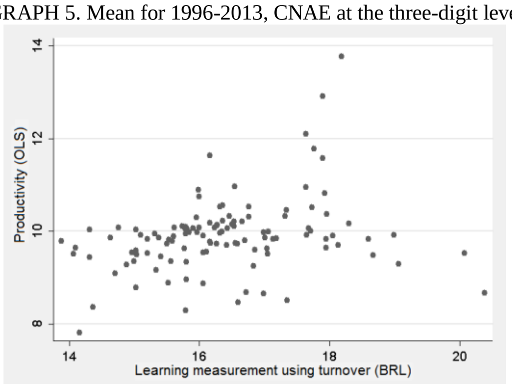


Source: RAIS (MTE) and PIA (IBGE). Own preparation

The positive trend is also observed in Graphs 3 and 4, in which productivity is measured by the Olley-Pakes and Levinsohn-Petrin methods, respectively. Therefore, as expected, despite the high dispersion among the different firms, a clear relationship between learning in a firm and productivity can be observed, regardless of the depreciation measurement used or the method by which TFP is estimated.

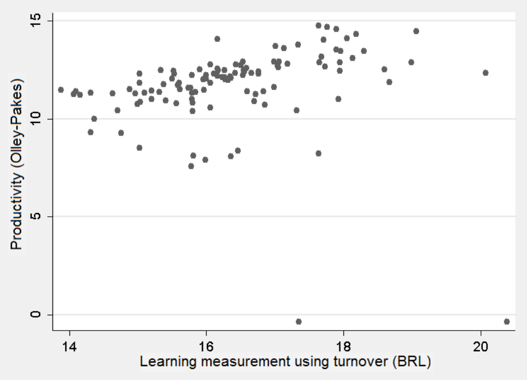
In Graphs 5-7, the relationships between TFP and learning are grouped at the three-digit level of the CNAE (112 groups). In the measurement of TFP by OLS, the relationship is dispersed between the groups; however, a positive trend can be observed. The dispersion decreases when using the Olley-Pakes method for calculating TFP, but the positive trend is maintained. The positive trend between the groups is also observed when using the Levinsohn-Petrin method.

GRAPH 5. Mean for 1996-2013, CNAE at the three-digit level



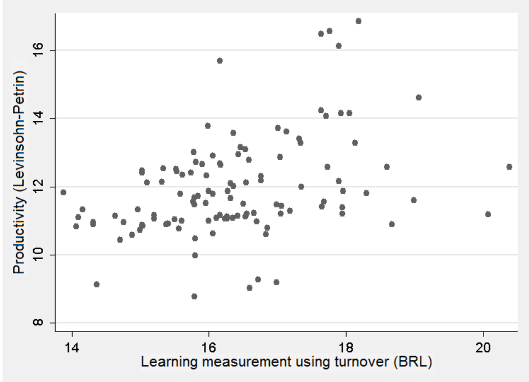
Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 6. Mean for 1996-2013, CNAE at the three-digit level



Source: RAIS (MTE) and PIA (IBGE). Own preparation

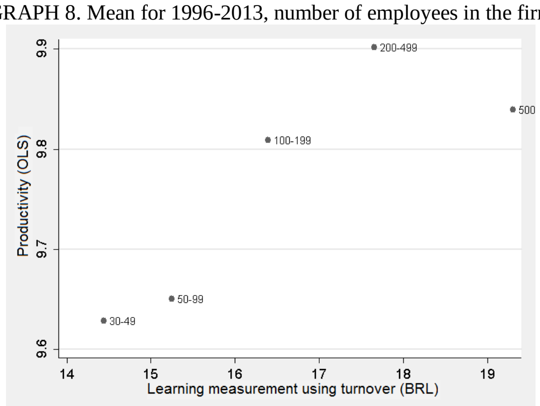
GRAPH 7. Mean for 1996-2013, CNAE at the three-digit level



Source: RAIS (MTE) and PIA (IBGE). Own preparation

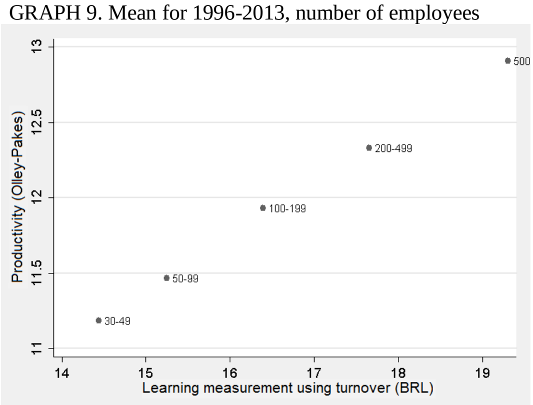
Finally, Graphs 8-10 show the mean of TFP and learning by firm size groups. We define firm size as the average number of employees that the firm has in the sample. The graphs show that there is a positive relationship between firm size and the learning measurement—the larger the firm is, the greater the capacity for the accumulation of knowledge. This advantage of large firms is reflected in their productivity. In the graphs, we can observe the positive relationship between firm size and the TFP measurements. Therefore, examining the size of firms, we have a highly positive relationship between the TFP measurements and the learning measurement.

GRAPH 8. Mean for 1996-2013, number of employees in the firm



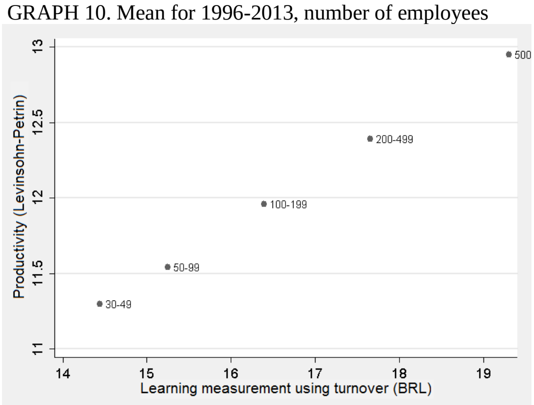
Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 9. Mean for 1996-2013, number of employees



Source: RAIS (MTE) and PIA (IBGE). Own preparation

GRAPH 10. Mean for 1996-2013, number of employees



Source: RAIS (MTE) and PIA (IBGE). Own preparation

3.2. Effect that learning in the firm has on productivity

The estimates presented here seek to isolate the effects of firm-specific learning on productivity. This was performed controlling for industry fixed effects; and also for the operating time, and general human capital, as calculated in section 4.2.1. Annual dummies are also included to control for macro shocks.

The results of equation 12, which estimates the effects of learning on TFP, are presented in Tables 2 and 3. The tables have three columns of results that show the three methods for calculating TFP. In Table 2, in which we use the turnover rate as a measurement of depreciation, the results indicate a significant positive relationship between learning and productivity. Table 3, which uses the separation rate as depreciation, also shows a positive and significant relationship between learning and productivity.

The results on the effects of learning are consistent and highly significant, with very close levels in the different analyses. When the dependent variable (TFP) is calculated by OLS (first columns of both tables), the learning effect approximately 11% (first row), regardless of how depreciation is considered in the learning measure. When the dependent variable (TFP) is calculated either by the Olley-Pakes or by the Levinsohn-Petrin methods, (second and third columns) the learning effect is greater than that calculated by OLS, and the elasticity is approximately 26%. General human capital has a positive and significant effect in all analyses. However, the magnitude of this effect is more sensible to the alternative measures for productivity and learning depreciation.

Finally, despite the negative sign and despite being significant, the “Entry year” variable, which captures the effect of the different times of entry of the firms, has almost zero effect.

TABLE 2. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.171***	0.349***	0.355***
	(0.002)	(0.002)	(0.002)
Human capital	0.613***	0.299***	0.152***
	(0.022)	(0.022)	(0.022)
Years of operation	-0.009***	-0.008***	-0.009***
	(0.000)	(0.000)	(0.000)
Constant	6.465***	6.377***	6.564***
	(0.038)	(0.039)	(0.038)
Observations	322,451	322,451	322,451
R-squared	0.521	0.790	0.729

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

TABLE 3. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.167***	0.339***	0.347***
	(0.002)	(0.002)	(0.002)
Human capital	0.665***	0.407***	0.255***
	(0.022)	(0.022)	(0.022)
Years of operation	-0.009***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)
Constant	6.455***	6.366***	6.529***
	(0.038)	(0.039)	(0.038)
Observations	310,266	310,266	310,266
R-squared	0.527	0.793	0.735

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

4. Robustness

4.1. Methodological Refinements

The estimation of (12) may be compromised by endogeneity for the learning term. Note that this term is a function of production in the previous period. As a consequence, it becomes a function of productivity in the previous period (as we have defined productivity as a component of production). If we assume that productivity has some temporal persistence (for example if it's evolution is approximated by an AR (1) process), chances are high that our learning term will be correlated with the error of the equation (1). This fact would bias the estimate for γ_e(our coefficient of interest) by OLS.

$$prod_{ijt} = \gamma_0 + \gamma_j + \gamma_v v_i + \gamma_t t + \gamma_h h_{it} + \gamma_e g(prod_{it-1}) + u_{ijt}$$

The introduction of a fixed effect would only complicate the matter further, since the necessary variables transformation to get rid of the fixed effect (first difference for example) would strength the correlation between the (transformed) error term and the (transformed) learning term. For the transformed model this correlation would hold even in the absence of any temporal persistence.[2]

Avoiding Endogeneity

As we have seen before, our theoretical framework underlining the productivity estimation assumes that production can be decomposed into a set of terms related to the use of factors, and an efficiency term that correspond to the productivity. On the other hand, in the theoretical framework that underlies the terms of learning, it is mentioned that this is determined precisely by the use of factors (in particular labor). Efficiency

[2] This is a problem widely discussed in economics since Nickel's seminal contribution (1981). Arellano and co-authors suggested in the 1990s ways to circumvent this problem with the aid of instrumental variables. However recent contributions in the literature of weak instruments show that these forms may aggravate the problem rather than attenuate it.

would not be a determinant of learning, but a consequence of it. Hence, an alternative measure of learning should purge the term of efficiency (productivity) from production. That is, we can define the following alternative measure to the learning term:

$$E_{it} = \delta(E_{it-1} + q_{it-1} - prod_{it-1}) \tag{14}$$

Equation (6) allow us to write the expression above as:

$$E_{it} = \delta(E_{it-1} + \beta_0 + \beta_K k_{it-1} + \beta_l l_{it-1}),$$

Which makes explicit the relation with the use of factors.

Note that the measure presented in (14) allows estimating a model analogous to that expressed in (12). Table 4 below report the results from that estimation where depreciation in learning is based on turn-over rate. We see that our previous results are robust, in the sense that the elasticity are still positive and relatively lower when PTF is estimated using OLS. Table 5 shows that the same conclusion applies once you use separation rate for depreciation.

TABLE 4. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.170***	0.342***	0.344***
	(0.002)	(0.002)	(0.002)
Human capital	0.617***	0.318***	0.181***
	(0.022)	(0.022)	(0.022)
Years of operation	-0.009***	-0.008***	-0.009***
	(0.000)	(0.000)	(0.000)
Constant	6.479***	6.467***	6.687***
	(0.038)	(0.038)	(0.039)
Observations	322,448	322,438	321,876
R-squared	0.520	0.789	0.719

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

TABLE 5. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.166***	0.333***	0.337***
	(0.002)	(0.002)	(0.002)
Human capital	0.668***	0.421***	0.279***
	(0.022)	(0.022)	(0.022)
Years of operation	-0.009***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)
Constant	6.468***	6.450***	6.645***
	(0.038)	(0.039)	(0.039)
Observations	310,267	310,262	309,843
R-squared	0.526	0.792	0.726

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

4.2. Human capital measurement

We have mentioned in section 2.2.3 two alternative ways to measure the human capital index of a firm. So far all the results were based in one of these procedures. The aim of this subsection is to show whether the results are sensible to this choice of variables. All the results so far were based on the index that use a higher education dummy combining complete secondary education with higher levels of education. The alternative measure considers the complete secondary education level in a dummy representing an intermediary level of education. Tables 6 and 7 brings results analogous to the ones shown in tables 4 and 5, but with this alternative way of considering secondary education in the human capital index. It is clear that our main conclusions are not affected by this choice of variable.

TABLE 6. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.168***	0.341***	0.343***
	(0.002)	(0.002)	(0.002)
Human capital (alternative)	0.688***	0.383***	0.218***
	(0.023)	(0.022)	(0.022)
Years of operation	-0.009***	-0.008***	-0.009***
	(0.000)	(0.000)	(0.000)
Constant	6.479***	6.432***	6.667***
	(0.036)	(0.036)	(0.036)
Observations	322,448	322,438	321,876
R-squared	0.522	0.789	0.719

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

TABLE 7. Effect of learning on the productivity of the firm

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.163***	0.331***	0.336***
	(0.002)	(0.002)	(0.002)
Human capital (alternative)	0.740***	0.491***	0.321***
	(0.023)	(0.022)	(0.022)
Years of operation	-0.009***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)
Constant	6.470***	6.421***	6.631***
	(0.037)	(0.036)	(0.036)
Observations	310,267	310,262	309,843
R-squared	0.527	0.792	0.726

Source: RAIS (MTE) and PIA (IBGE), 1996–2013.
Notes:
Standard error between parentheses
Significance: *** p<0.01, ** p<0.05, * p<0.1
Fixed effect: CNAE 4 digits

Final considerations

The recent growth of the Brazilian economy has occurred with low productivity gains, even compared to other countries with a similar level of development. One possible explanation is high labor turnover, which has negative effects on learning. This excessive movement between jobs is associated with low levels of commitment and investment in professional training, both by workers and by firms, with consequences for labor productivity.

In this paper, we studied the effect that high turnover in the job market had on the productivity of Brazilian manufacturing firms between 1996 and 2013. Initially, a description of the behavior of the turnover rate for the Brazilian job market in recent decades was presented. The turnover rate has remained high and was indicated as one of the obstacles to productivity growth.

We used the learning by doing literature, which claims that intra-firm productivity gains can occur through efficiency gains achieved via the accumulation of learning that results from the act of producing. We estimated a learning measurement for capturing the loss of human capital, resulting from turnover, and the effect that this has on TFP.

TFP was calculated using three different methods: OLS, the Olley-Pakes method, and the Levinsohn-Petrin method. By correlating our learning measurement with the TFP estimates, we found a positive relationship using different specifications.

In the empirical analysis, we sought to isolate the specific human capital of workers in the learning variable, using an estimate of general human capital as a control. Thus, as a result, we have a more precise effect from the learning accumulated during the production performed in the firm. The final results show that the estimated learning measurement, in which turnover impacts negatively, has a positive effect on TFP. We have an indication of the importance of firm-specific learning for obtaining productivity gains in industry.

Thus, one method of leveraging productivity in Brazil would be through the implementation of public policies that prioritize measures aimed at reducing rates of job turnover and increasing the degree of negotiation between firms and employees.

Bibliographical references

ABOWD, J. M.; HALTIWANGER, J.; JARMIN, R.; LANE, J.; LENGERMANN P.; MCCUE, K.; MCKINNEY, K.; SANDUSKY, K. 2005. "The Relationship Between Human Capital, Productivity and Market Value: Building Up form Micro Evidence". Em: “Measuring Capital in the New Economy”, pages 153–204. University of Chicago Press.

ARGOTE, L.; BECKMAN, S. L; EPPLE, D. 1990. "The Persistence and Transfer of Learning in Industrial Settings". Management Science, February, 36. p. 140-54.

ARROW, K. J. (1962) "The Economic Implications of Learning by Doing" Review of Economic Studies, June, 29, 155-173.

BANCO CENTRAL DO BRASIL – BCB (2012); “Evidências do Aumento de Escolaridade Média da Força de Trabalho”. Relatório de Inflação, June, 2012.

BECKER, G. S. 1962. “Investment in human capital: A theoretical analysis”. The journal of political economy, 9-49.

_________. 1993. “Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education”. Third edition, Chicago and London, University of Chicago Press.

BENKARD, C. L. 2000. "Learning and Forgetting: The Dynamics of Aircraft Production," American Economic Review, September, 90. p. 1034-54.

BRACHET, T.; DAVID, G. 2011. “On the determinants of organizational forgetting”. American Economic Journal: Microeconomics, v. 3, n. 3, p. 100-123.

CHIANG, H. (2004) “Learning by Doing, Worker Turnover, and Productivity Dynamics”. Econometric Society, No 593.

CORSEUIL, C. H.; FOGUEL, M. 2011. “Expansão econômica e aumento da formalização das relações de trabalho: uma abordagem através das contratações”. IPEA, Rio de Janeiro. (Texto para Discussão, nº 1571)

CORSEUIL, C. H.; FOGUEL, M.; GONZAGA, G.; RIBEIRO, E. P. (2013); “A rotatividade dos jovens no mercado de trabalho formal brasileiro”. Anais do 41º Encontro Nacional de Economia, Anpec.

GATHMANN, C.; SCHONBERG, U. 2010. “How general is human capital? A task-based approach”. Journal of Labor Economics , v. 28, n. 1, p. 1-49.

GONZAGA, G. 2003. “Labor Turnover and Labor Legislation in Brazil”. Economía, v. 4, n. 1, p. 165-222.

GONZAGA, G.; PINTO, R. C. 2014. “Rotatividade do Trabalho e Incentivos da Legislação Trabalhista”. Em: BONELLI, R.; VELOSO, F. Veloso (orgs.). “Panorama do mercado de trabalho no Brasil”, Rio de Janeiro.

GUTHRIE, J. P. 2001. “High-involvement work practices, turnover, and productivity: Evidence from New Zealand.” Academy of management Journal, v. 44, n. 1, p. 180-190.

HECKMAN, J.; LOCHNER, L.; COSSA, R. 2002. “Learning by doing vs. on-the-job training: using variation induced by the EITC to distinguish between models of skill formation”. National Bureau of Economic Research.

HECKMAN, J. J.; LOCHNER, L.; TODD, P. E. 2006. “Earnings functions, rates of return and treatment effects: The mincer equation and b eyond”. Elsevier, v.1, 1st ed., chap. 07, p. 307-458.

INSTITUTO DE PESQUISA ECONÔMICA APLICADA – IPEA. 2012. “Produtividade no Brasil nos anos 2000-2009: análise das Contas Nacionais”. Comunicados do IPEA nº 133.

LEVINSOHN, J.; PETRIN, A. 2003. “Estimating production functions using inputs to control for unobservables.” Review of Economic Studies, v. 70, n. 2, p. 317-341.

LEVITT, S. D.; LIST, J. A.; SYVERSON, C. 2012. “Toward an understanding of learning by doing: Evidence from an automobile assembly plant.” National Bureau of Economic Research.

MESSA, A. 2014. “Metodologias de Cálculo da Produtividade Total dos Fatores e da Produtividade da Mão de Obra”. In: NEGRI, F.; CAVALCANTE, L. R. (Comp.). Produtividade no Brasil: Desempenho e Determinantes. Brasília: Abdi, Ipea. Cap. 3. p. 87-110.

MINCER, J. A. 1974. “Schooling, experience, and earnings”. NBER, 1974. p. 41-63.

Olley, G. S., and A. Pakes. 1996. “The dynamics of productivity in the telecommunications equipment industry”. Econometrica 64: 1263–1297.

ORELLANO, V. I. F.; PAZELLO, E. T. 2006. “Evolução e determinantes da rotatividade da mão-de-obra nas firmas da indústria paulista na década de 1990.” Pesquisa e Planejamento Econômico. Rio de Janeiro, v. 36, n. 1, p. 179-207, apr.

PRESTON, L. E.; KEACHIE, E. C. 1964. “Cost functions and progress functions: An integration.” The American Economic Review, v. 54, n. 2, p. 100-107.

RAPPING, L. 1965. “Learning and World War II production functions.” The Review of Economics and Statistics, p. 81-86.

SCHULTZ, T. W. 1961. “Investment in human capital.” The American Economic Review, p. 1-17.

THOMPSON, P. 2007. “How much did the Liberty shipbuilders forget?”. Management Science, v. 53, n. 6, p. 908-918.

WRIGHT, T. P. 1936. "Factors Affecting the Cost of Airplanes". Aeronautical Sci. 3 Feb. p.122-28.

YAMAGUCHI, S. 2012. “Task and heterogeneous human capital”. Journal of Labor Economics , v. 30, n. 1, p. 1-53.