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Article

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EconomiA

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Suggested Citation: da Rocha, Leandro Pereira; Pero, Valéria; Corseuil, Carlos Henrique (2019) : Turnover, learning by doing, and the dynamics of productivity in Brazil, *EconomiA*, ISSN 1517-7580, Elsevier, Amsterdam, Vol. 20, Iss. 3, pp. 191-210, <https://doi.org/10.1016/j.econ.2019.11.001>

This Version is available at:

<https://hdl.handle.net/10419/266944>

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Turnover, learning by doing, and the dynamics of productivity in Brazil

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Received 30 July 2018; received in revised form 15 April 2019; accepted 22 November 2019

Available online 23 December 2019

Abstract

This article analyses the effect of labor turnover on the productivity of Brazilian manufacturing firms between 1996 and 2013. We based our analysis on a theory of learning by doing, where turnover harms productivity by restricting the efficiency gains achieved by workers when they accumulate learning by 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: Learning by doing; Labor turnover; Productivity

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1. Introduction

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 in Brazil was marked by the sound performance of the economy and the job market, with an increase in formal employment and a decrease in unemployment rates (Corseuil and Foguel, 2011). In addition, the increase in the educational level of the work force that occurred in the 90s continued during the 2000s. However, despite these many improvements in the labor market related outcomes; there was a stagnation of labor productivity during this period (IPEA, 2012).

Accordingly, the high rate of job turnover has been indicated as a cap on the growth of labor productivity in Brazil (Gonzaga and Pinto, 2014; Corseuil et al., 2013). As a matter of fact, an increase in the turnover rate was another worrisome trend in Brazil during the 2000s years. There are at least two channels through which labor turnover may harm productivity at micro level. The first one is through its effects on the accumulation of knowledge at firm level;

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referred here as learning. But high turnover may also have undermining consequences for labor productivity through low levels of commitment and investment in professional training, both by workers and by firms, as future benefits would be heavily discounted in a high labor turnover environment.

The main objective of this paper is to understand the effects of labor turnover on productivity at micro level through the learning channel. To that end, we estimate a learning component measurement that takes into account the loss of knowledge resulting from turnover.

There are two main branches of the literature relating knowledge accumulation and productivity growth, at micro level. The first is the human capital theory (Schultz, 1961; Becker, 1962), which postulates how labor productivity at individual level grows according to skill accumulation. Individual education level plays a fundamental role for this theory, as well as labor market experience. Schooling enables the acquisition of general knowledge, which is complemented by the specific knowledge acquired by the individual along his active life cycle. This specific knowledge can, in turn, be acquired through on-the-job experience and training or through specialized courses. The empirical counterpart of this literature relates education and experience to wage at individual level. A huge amount of papers since Mincer (1974) confirm the predictions. In particular, it is confirmed that wage (hence labor productivity) grows with tenure (Altonji and Shakotko, 1987).¹ This branch of the literature poses turnover as a detrimental factor for individual wage (and welfare) growth.

The second one is the “learning by doing” theory (Arrow, 1962), which postulates how productivity at firm level grows according to practical experience acquired during the production process. The mechanism posed by Arrow can be summarized in the following sentence: “it is the very activity of production which gives rise to problems for which favorable responses are selected over time” (Arrow – Apud Thompson, 2012). According to this view individual learning is part of a more general process named “organizational learning”. This has inspired another considerable amount of empirical papers relating unitary cost of production (as a proxy for productivity) to accumulated quantity produced. Thompson (2012) surveys critically these empirical papers noting that the first academic contribution dates back to Wright (1936). According to him the evidence is far from conclusive, at least with respect to two issues. First, the learning does not seem to last for a long time horizon. Second, learning seems not to be a continuous process, as formulated in the standard formulation of the empirical models.² There are evidence favoring interruptions along the learning curve.

Thompson (2007) cites three reasons for the occurrence of interruptions, or 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. Therefore a new generation of papers decided to check how important is learning depreciation or “forgetting”, relying on information about labor turnover. Chiang (2004); Brachet and David (2011) are crucial papers along this line.³ The later finds that labor turnover is much more important as a source of organizational “forgetting” than skill losses or depreciation of workers retained by ambulance companies in Michigan. We therefore follow the approach of Chiang (2004) who considers an empirical measure of learning based on output accumulation and discounted by turnover rates. The author relates this learning measure to total factor productivity at firm level. The main advantage of his approach is the possibility to pool together information for many different industries, as opposed to a specific narrowly defined industry which was the standard in the literature.

In the following section we expose our database, accomplishing the construction of our main variables; as well as the specification of our empirical model relating learning to total factor productivity. The results obtained for this relation is the focus of the third section. We confirm a positive relation between learning and productivity even after taking into account the possibility of “forgetting” due to labor turnover. The fourth section is dedicated to a methodological challenge commonly pointed to this literature, which is related to a possible endogeneity of the learning variable. We propose an alternative model and show that results are robust across model specifications. The final section brings our conclusions.

¹ More recent development of this literature shows heterogeneous tenure effects on wages, depending on worker schooling level (Heckman et al., 2006) or task performed (Gathmann and Schonberg, 2010; Guanziroli and Gonzaga, 2017).

² According to the standard formulation the cost declines with production according to the power rule.

³ Benkard (2000) is also an important reference in this literature, but has relied in a constant forgetting rate rather than using data on turnover.

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 employees and jobs 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 firm to obtain the indicators related to the characteristics of the firm. At this level, only firms that operate in the manufacturing sector are filtered to continue so that the database will 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 2.0⁴ 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 with the substitution of one worker by another in the same job. The empirical counterpart of this concept is generally measured using the following formula:

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

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:

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

⁴ 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.

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).

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

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; it reached its peak in 2008 and decreased slightly in 2009 due to the effects of the international crisis; from 2010 onward, the turnover rate remained at higher levels, ranging 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 potential for this learning to 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:

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

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 $t-1$, measured in Gross Production Value (GPV). The “depreciation” of learning is represented by δ_t , which is bounded between 0 and 1. Note that we allow for time variation in depreciation, which contrasts with a standard assumption of a fixed rate for 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:

$$E_{it} = (1 - tr_{it-1})(E_{it-1} + q_{it-1}) \quad (2)$$

In one extreme case, if in 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.

Table 2
Learning measurements. 1997–2013.

Year	Learning measurement (turnover rate)					Learning measurement (termination rate)				
	Mean	Standard deviation	10th percentile	Median	90th percentile	Mean	Standard deviation	10th percentile	Median	90th percentile
1997	14.36	1.66	12.42	14.19	16.60	14.25	1.68	12.27	14.10	16.52
1998	14.74	1.76	12.62	14.61	17.09	14.58	1.80	12.38	14.46	16.97
1999	15.05	1.81	12.83	14.96	17.43	14.83	1.84	12.58	14.76	17.26
2000	15.29	1.87	12.94	15.23	17.75	15.07	1.89	12.72	15.01	17.54
2001	15.34	1.95	12.88	15.31	17.89	15.16	1.97	12.70	15.11	17.71
2002	15.40	2.00	12.85	15.38	17.99	15.21	2.02	12.67	15.17	17.83
2003	15.46	2.04	12.89	15.42	18.13	15.27	2.06	12.70	15.22	17.97
2004	15.58	2.07	12.98	15.55	18.28	15.40	2.10	12.79	15.35	18.14
2005	15.66	2.11	12.97	15.64	18.42	15.50	2.14	12.81	15.46	18.32
2006	15.72	2.14	13.05	15.68	18.52	15.56	2.16	12.88	15.48	18.41
2007	15.81	2.12	13.18	15.76	18.61	15.65	2.15	13.00	15.57	18.47
2008	15.83	2.14	13.19	15.74	18.62	15.67	2.17	13.01	15.58	18.52
2009	15.80	2.14	13.18	15.70	18.59	15.64	2.16	13.02	15.52	18.48
2010	15.83	2.13	13.24	15.70	18.64	15.62	2.15	13.04	15.47	18.47
2011	15.79	2.14	13.21	15.63	18.61	15.63	2.16	13.03	15.46	18.48
2012	15.96	2.14	13.33	15.87	18.74	15.80	2.15	13.19	15.70	18.62
2013	16.01	2.12	13.42	15.90	18.79	15.83	2.15	13.23	15.70	18.63
All the Years	15.56	2.08	13.01	15.43	18.31	15.39	2.11	12.82	15.25	18.17

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

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 dismissal of workers has on firms, we use a learning measurement that uses the separation rate (sr) instead of the turnover rate for depreciation:

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

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.

Table 2 shows the evolution of a series of statistics for the learning measurements that use the turnover rate and the separation rate. Both measurements evolved between 1997 and 2013. The measurement using the turnover has higher levels and lower standard deviations.

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 et al. (2005) and Chiang (2004) estimate human capital via the following model:

$$w_{ait} = x_{ait}\beta + \varphi_i + \varepsilon_{ait} \quad (4)$$

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,

Table 3
Measures of General Humssan Capital, 1996–2013.

Year	Average wage ^a	Human capital (Measurement 1)	Human capital (Measurement 2)
1996	645.70	1.58	1.46
1997	724.70	1.59	1.48
1998	728.40	1.60	1.49
1999	701.10	1.61	1.50
2000	736.70	1.62	1.50
2001	730.10	1.62	1.50
2002	725.50	1.64	1.51
2003	769.20	1.65	1.52
2004	810.40	1.66	1.53
2005	829.60	1.68	1.54
2006	793.30	1.69	1.55
2007	761.20	1.70	1.55
2008	775.80	1.71	1.55
2009	782.70	1.73	1.57
2010	770.00	1.74	1.57
2011	847.10	1.75	1.57
2012	871.70	1.76	1.58
2013	897.60	1.77	1.59

Source: RAIS (MTE).

^a Prices from 2013.

whereas others, such as education and some unobserved components (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 we will call h , is formed by combining the observable component of the individuals using the estimated parameters from Eq. 4 ($\hat{\beta}$). Thus, we have the following:

$$h_{ait} = x_{ait} \hat{\beta} \quad (5)$$

We use two measurements of general human capital. The difference between them is in the specification of the education dummies. The first dummy 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. 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.

Table 3 shows the evolution of these two measurements of general human capital and their main components. It can be observed that the trajectories of wages are not very closely linked to the evolution of human capital measurements between 1996 and 2013. That is surprising, but it reminds us that the evolution of wages has also been remarkably different from that of labor productivity in Brazil over this same period.

2.2.4. Total factor productivity

For the productivity measurement, we follow the approaches of [Messa \(2014\)](#), who calculates total factor productivity (TFP) using econometric methods applied to Brazilian manufacturing plant level data. Starting with a Cobb-Douglas production function, such that the product (Y) of firm i at time t is a result of the combination of 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. This study adopts the following three estimates, which are commonly utilized in the literature: (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 for 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 obtain the following:

$$y_{it} = \beta_0 + \beta_K k_{it} + \beta_l l_{it} + \varepsilon_{it} \quad (6)$$

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 violate certain assumptions of the OLS method and yield biased estimators.

When estimating the production function, the error term (the deviations in relation to the mean) of the equation that is being associated with 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 [Olley and Pakes \(1996\)](#) and [Levinsohn and Petrin \(2003\)](#) methods.

i) 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 the 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:

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

where $\varphi(i_{it}, k_{it}) = \beta_K k_{it} + g(i_{it}, k_{it})$

where φ can be estimated by a third-order polynomial. Thus, from (7), we obtain the estimate $\hat{\beta}_l$. 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:

$$y_{it} - \hat{\beta}_l l_{it} = \beta_K k_{it} + h(\varphi_{it-1} - \beta_K k_{it}) + \zeta_{it} + \vartheta_{it} \quad (8)$$

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

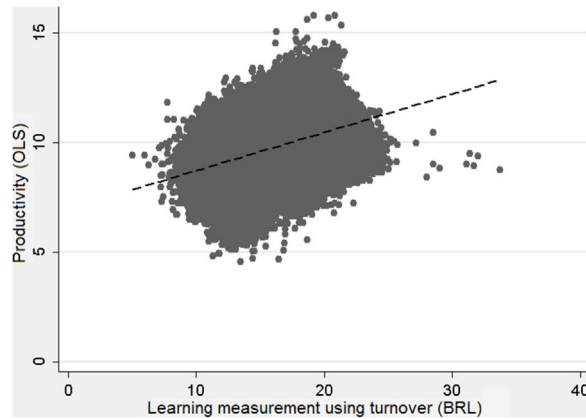
i) Levinsohn-Petrin Method

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 are 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 variable i —which represents the investment flows—with variable m , which represents the intermediate costs, such that $m_{it} = f(m_{it}, k_{it})$. Thus, we obtain the estimate of $\hat{\beta}_l$.

For the second stage, any candidate β_K^* is used, with the objective of computing a predicted value for ω_t for all periods t :

$$\hat{\omega}_{it} = y_{it} - \beta_K^* k_{it} - \hat{\beta}_l l_{it} \quad (9)$$



Graph 1. Mean of TFP using OLS and of learning using the turnover rate (1996–2013).
Source: RAIS (MTE) and PIA (IBGE). Own preparation.

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.

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

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

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

Table 4 shows the evolution, between 1996 and 2013, of a series of statistics for the three methods of calculating TFP used in this study. The OLS method has a log value of 9.956 in 2013—higher than the mean of the period (9.710)—and has, on average, a lower standard deviation. The Olley-Pakes and Levinsohn-Petrin methods have higher levels, with values of 11.810 and 11.890, respectively, in 2013, which are also higher than the values of all of the years analyzed.

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:

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

where $prod_{ijt}$ is the measure of 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 the 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, $e_{it} = \log(E_{it})$. Last, 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 1.2.4.

3.1. Relationship between learning and productivity

Graph 1–4 are plotted pooling information from all firms in the sample. In Graphs 1 and 2, productivity is estimated using OLS while learning is measured using depreciation based on turnover rate in Graph 1 and separation rate in

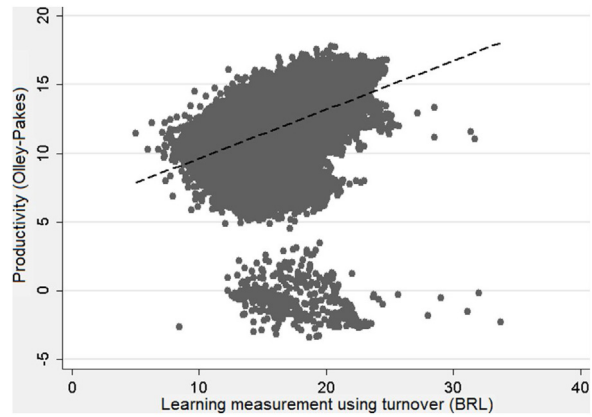
Table 4
Total Factor Productivity (TFP), 1996–2013.

Year	Ordinary Least Squares (OLS)					Olley-Pakes					Levinsohn-Petrin				
	Mean	Standard deviation	10th percentile	Median	90th percentile	Mean	Standard deviation	10th percentile	Median	90th percentile	Mean	Standard deviation	10th percentile	Median	90th percentile
1996	9.58	0.95	8.33	9.66	10.64	11.43	1.55	9.52	11.57	13.11	11.47	1.39	9.90	11.37	13.13
1997	9.66	0.98	8.40	9.74	10.76	11.53	1.58	9.66	11.67	13.23	11.61	1.39	10.03	11.51	13.28
1998	9.70	0.99	8.39	9.79	10.84	11.53	1.57	9.66	11.67	13.24	11.60	1.37	10.01	11.51	13.29
1999	9.60	0.99	8.30	9.69	10.77	11.43	1.56	9.66	11.54	13.17	11.51	1.34	9.94	11.43	13.17
2000	9.64	1.00	8.32	9.73	10.83	11.48	1.57	9.66	11.58	13.26	11.58	1.35	10.00	11.48	13.26
2001	9.64	1.01	8.32	9.73	10.83	11.45	1.54	9.70	11.54	13.22	11.56	1.33	10.01	11.47	13.22
2002	9.52	1.01	8.21	9.60	10.72	11.32	1.51	9.65	11.37	13.07	11.43	1.30	9.89	11.35	13.05
2003	9.58	1.00	8.30	9.66	10.79	11.36	1.52	9.69	11.40	13.14	11.47	1.31	9.92	11.39	13.11
2004	9.57	1.00	8.28	9.63	10.78	11.35	1.52	9.68	11.39	13.13	11.46	1.30	9.90	11.37	13.12
2005	9.62	0.98	8.36	9.67	10.83	11.39	1.52	9.71	11.42	13.18	11.51	1.30	9.93	11.40	13.16
2006	9.65	0.97	8.41	9.68	10.83	11.41	1.50	9.79	11.45	13.17	11.54	1.28	10.01	11.45	13.15
2007	9.68	0.98	8.45	9.73	10.87	11.50	1.48	9.92	11.52	13.25	11.61	1.29	10.07	11.53	13.23
2008	9.72	0.98	8.47	9.76	10.92	11.59	1.40	10.06	11.58	13.28	11.63	1.27	10.14	11.55	13.22
2009	9.74	0.97	8.52	9.77	10.92	11.59	1.38	10.09	11.59	13.26	11.64	1.24	10.16	11.57	13.19
2010	9.78	0.95	8.58	9.83	10.95	11.66	1.35	10.20	11.65	13.28	11.72	1.22	10.27	11.65	13.23
2011	9.87	0.95	8.68	9.91	11.04	11.72	1.32	10.28	11.71	13.29	11.81	1.19	10.38	11.73	13.28
2012	9.96	0.93	8.79	9.98	11.11	11.81	1.28	10.43	11.80	13.32	11.91	1.15	10.52	11.83	13.35
2013	9.96	0.94	8.77	9.98	11.12	11.81	1.29	10.43	11.80	13.34	11.89	1.17	10.49	11.81	13.36
All the Years	9.71	0.98	8.45	9.76	10.89	11.54	1.47	9.93	11.59	13.23	11.63	1.29	10.10	11.55	13.22

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



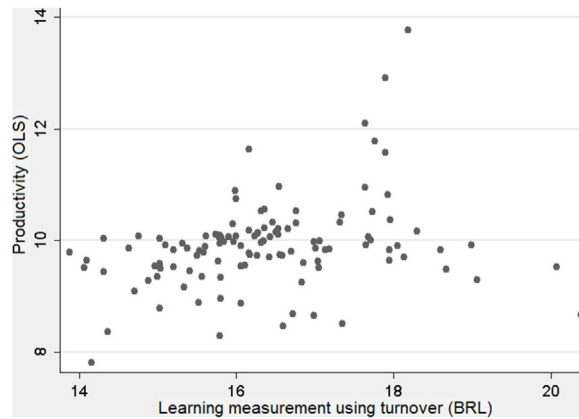
Graph 2. Mean of TFP using OLS and of learning using the separation rate (1996–2013).
Source: RAIS (MTE) and PIA (IBGE). Own preparation



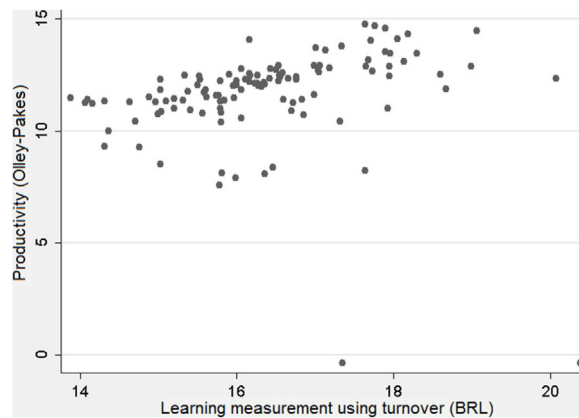
Graph 3. Mean of TFP using Olley-Pakes and of learning using the turnover rate (1996–2013).
Source: RAIS (MTE) and PIA (IBGE). Own preparation



Graph 4. Mean of TFP using Levinsohn-Petrin and of learning using the turnover rate (1996–2013).
Source: RAIS (MTE) and PIA (IBGE). Own preparation



Graph 5. Mean of TFP using OLS and of learning using the turnover rate, according to Cnae at the three-digit level (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation



Graph 6. Mean of TFP using Olley-Pakes and of learning using the turnover rate, according to Cnae at the three-digit level (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation

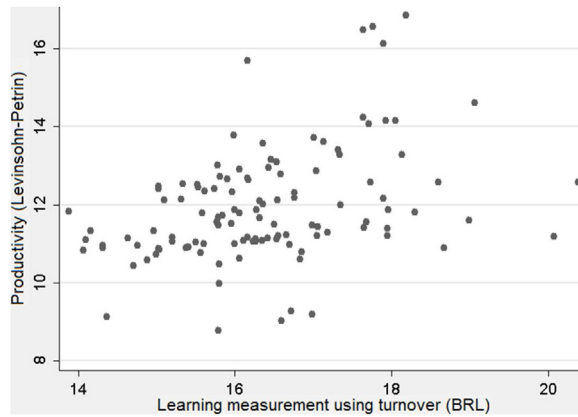
Graph 2. In both graphs, there is extensive dispersion between firms, but the relationship between learning and TFP shows a clear positive trend. Both learning measurements show very similar correlations with TFP. Therefore, the remaining graphs will be shown with only the learning measurement that uses the turnover rate as depreciation.

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.

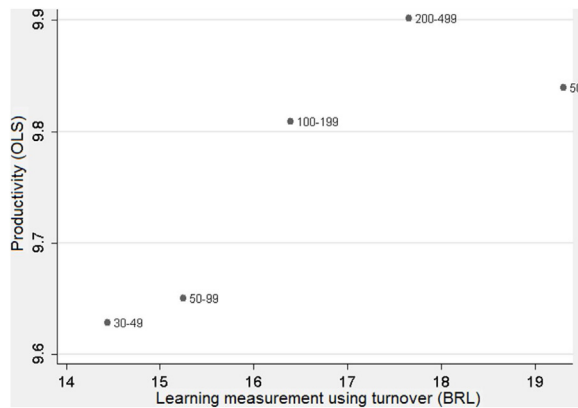
Therefore, as expected, despite the high dispersion among the different firms, a clear relationship between learning in a firm and productivity can be observed, regardless of the depreciation measurement used or the method by which TFP is estimated.

In [Graph 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.

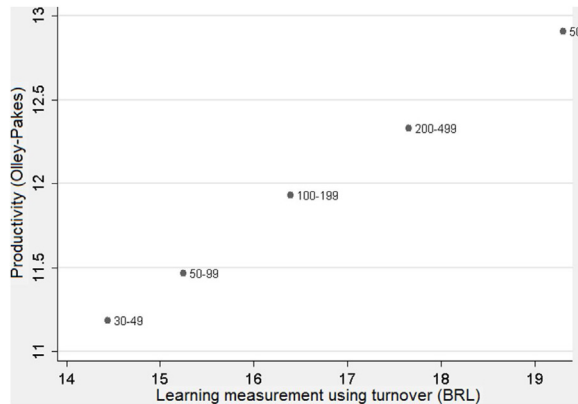
Finally, [Graph 8–10](#) show the mean of TFP and learning by firm size groups. We define firm size as the average number of employees that the firm has in the sample. The graphs show that there is a positive relationship between firm size and the learning measurement—the larger the firm is, the greater 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 TFP. Therefore, examining the size of firms, we have a highly positive relationship between the TFP measurement and the learning measurement.



Graph 7. Mean of TFP using Levinsohn-Petrin and of learning using the turnover rate, according to Cnae at the three-digit level (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation



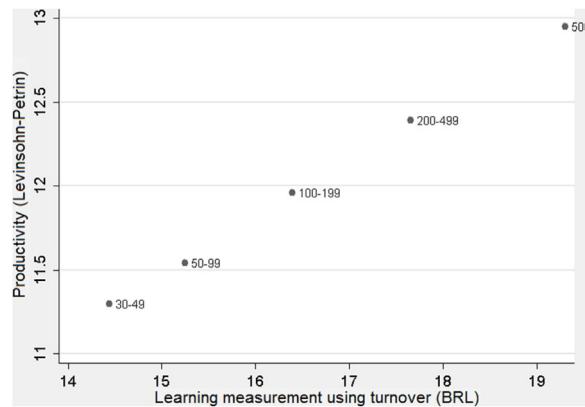
Graph 8. Mean of TFP using OLS and of learning using the turnover rate, by firm size groups (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation



Graph 9. Mean of TFP using Olley-Pakes and of learning using the turnover rate, by firm size groups (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation

3.2. Estimated effects of firm-specific learning on productivity

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



Graph 10. Mean of TFP using Levinsohn-Petrin and of learning using the turnover rate, by firm size groups (1996–2013). Source: RAIS (MTE) and PIA (IBGE). Own preparation

The results of Eq. (12), which estimates the effects of learning on TFP, are presented in Tables 5 and 6. The tables have three columns of results that show the three methods for calculating TFP. In Table 5, in which we use the turnover rate as the measurement of depreciation, the results indicate a significant positive relationship between learning and productivity. Table 6, 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 between the different analyses. When the dependent variable (TFP) is calculated by OLS (first columns of both tables), the learning effect is approximately 11% (first row), regardless of how depreciation is considered in the learning measure. When the dependent variable (TFP) is calculated by either the Olley-Pakes or 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 compared 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 years of firm entry, has almost zero effect.

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 — or example, if its evolution is approximated by an auto AR (1) process (autoregressive model of order 1 process) —, chances are high that our learning term will be correlated with the error of Eq. (1). This would bias the OLS estimate for γ_e (our coefficient of interest).

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

The introduction of a fixed effect would only complicate the matter further, since the necessary variable transformation to eliminate the fixed effect (the first difference, for example) would strengthen 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.⁵

⁵ This is a problem widely discussed in economics since Nickel’s seminal contribution (1981). In the 1990s, Arellano and co-authors suggested 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.

Table 5
Effect of learning on firm productivity using the turnover rate.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.171*** (0.002)	0.349*** (0.002)	0.355*** (0.002)
Human capital	0.613*** (0.022)	0.299*** (0.022)	0.152*** (0.022)
Years of operation	−0.009*** (0.000)	−0.008*** (0.000)	−0.009*** (0.000)
1998	−0.022*** (0.004)	−0.132*** (0.004)	−0.138*** (0.004)
1999	−0.170*** (0.005)	−0.332*** (0.005)	−0.332*** (0.005)
2000	−0.170*** (0.006)	−0.356*** (0.006)	−0.343*** (0.006)
2001	−0.193*** (0.006)	−0.410*** (0.006)	−0.385*** (0.006)
2002	−0.347*** (0.007)	−0.582*** (0.007)	−0.552*** (0.007)
2003	−0.304*** (0.007)	−0.566*** (0.007)	−0.528*** (0.007)
2004	−0.350*** (0.007)	−0.625*** (0.007)	−0.576*** (0.007)
2005	−0.339*** (0.007)	−0.629*** (0.007)	−0.572*** (0.007)
2006	−0.333*** (0.007)	−0.641*** (0.007)	−0.575*** (0.007)
2007	−0.317*** (0.007)	−0.627*** (0.007)	−0.551*** (0.007)
2008	−0.295*** (0.008)	−0.620*** (0.008)	−0.539*** (0.008)
2009	−0.274*** (0.008)	−0.606*** (0.008)	−0.523*** (0.008)
2010	−0.239*** (0.008)	−0.570*** (0.008)	−0.476*** (0.008)
2011	−0.171*** (0.008)	−0.523*** (0.008)	−0.410*** (0.008)
2012	−0.130*** (0.008)	−0.498*** (0.008)	−0.370*** (0.008)
2013	−0.121*** (0.008)	−0.511*** (0.008)	−0.375*** (0.009)
Constant	6.465*** (0.038)	6.377*** (0.039)	6.564*** (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.

4.1.1. Avoiding endogeneity

As we have seen earlier, our theoretical framework underlying 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 corresponds to productivity. In the theoretical framework that underlies the terms of learning, it is mentioned that this is determined specifically by the use of factors (in particular, labor). Efficiency would not be a determinant of learning, but a consequence of it.

Table 6
Effect of learning on firm productivity using the separation rate.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.167*** (0.002)	0.339*** (0.002)	0.347*** (0.002)
Human capital	0.665*** (0.022)	0.407*** (0.022)	0.255*** (0.022)
Years of operation	–0.009*** (0.000)	–0.007*** (0.000)	–0.008*** (0.000)
1998	–0.014*** (0.005)	–0.109*** (0.005)	–0.113*** (0.005)
1999	–0.152*** (0.005)	–0.288*** (0.005)	–0.287*** (0.005)
2000	–0.153*** (0.006)	–0.317*** (0.006)	–0.304*** (0.006)
2001	–0.180*** (0.006)	–0.380*** (0.006)	–0.357*** (0.006)
2002	–0.332*** (0.007)	–0.549*** (0.007)	–0.519*** (0.007)
2003	–0.288*** (0.007)	–0.532*** (0.007)	–0.495*** (0.007)
2004	–0.331*** (0.007)	–0.588*** (0.007)	–0.540*** (0.007)
2005	–0.326*** (0.007)	–0.603*** (0.007)	–0.548*** (0.007)
2006	–0.320*** (0.007)	–0.611*** (0.007)	–0.549*** (0.007)
2007	–0.307*** (0.007)	–0.602*** (0.007)	–0.528*** (0.007)
2008	–0.285*** (0.008)	–0.596*** (0.008)	–0.516*** (0.008)
2009	–0.261*** (0.008)	–0.581*** (0.008)	–0.499*** (0.008)
2010	–0.221*** (0.008)	–0.534*** (0.008)	–0.442*** (0.008)
2011	–0.163*** (0.008)	–0.503*** (0.008)	–0.393*** (0.008)
2012	–0.123*** (0.008)	–0.479*** (0.008)	–0.353*** (0.008)
2013	–0.108*** (0.008)	–0.484*** (0.008)	–0.350*** (0.009)
Constant	6.455*** (0.038)	6.366*** (0.039)	6.529*** (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.

Hence, an alternative measure of learning should purge the term for efficiency (productivity) from production. That is, we can define the following alternative measure to the learning term:

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

Eq. (6) allows us to write the expression above as:

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

Table 7
Effect of the alternative learning measure on firm productivity using the turnover rate.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.170*** (0.002)	0.342*** (0.002)	0.344*** (0.002)
Human capital	0.617*** (0.022)	0.318*** (0.022)	0.181*** (0.022)
Years of operation	−0.009*** (0.000)	−0.008*** (0.000)	−0.009*** (0.000)
1998	−0.021*** (0.004)	−0.128*** (0.004)	−0.131*** (0.004)
1999	−0.169*** (0.005)	−0.326*** (0.005)	−0.318*** (0.005)
2000	−0.169*** (0.006)	−0.352*** (0.006)	−0.328*** (0.006)
2001	−0.192*** (0.006)	−0.406*** (0.006)	−0.369*** (0.006)
2002	−0.346*** (0.007)	−0.579*** (0.007)	−0.535*** (0.007)
2003	−0.302*** (0.007)	−0.565*** (0.007)	−0.514*** (0.007)
2004	−0.349*** (0.007)	−0.626*** (0.007)	−0.563*** (0.007)
2005	−0.338*** (0.007)	−0.631*** (0.007)	−0.562*** (0.007)
2006	−0.331*** (0.007)	−0.643*** (0.007)	−0.565*** (0.007)
2007	−0.316*** (0.007)	−0.630*** (0.007)	−0.543*** (0.007)
2008	−0.294*** (0.008)	−0.624*** (0.008)	−0.531*** (0.008)
2009	−0.272*** (0.008)	−0.612*** (0.008)	−0.517*** (0.008)
2010	−0.238*** (0.008)	−0.576*** (0.008)	−0.469*** (0.008)
2011	−0.170*** (0.008)	−0.529*** (0.008)	−0.405*** (0.008)
2012	−0.129*** (0.008)	−0.504*** (0.008)	−0.364*** (0.008)
2013	−0.120*** (0.008)	−0.517*** (0.008)	−0.368*** (0.009)
Constant	6.479*** (0.038)	6.467*** (0.038)	6.687*** (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.

Which makes explicit the relation with the use of factors.

Note that the measure presented in (14) allows estimation of a model analogous to that expressed in (12). Table 7 below reports the results from that estimation, where depreciation in learning is based on turnover rate. We see that our previous results are robust, in the sense that elasticity is still positive and relatively lower when PTF is estimated using OLS. Table 8 shows that the same conclusion applies once you use the separation rate for depreciation.

Table 8
Effect of the alternative learning measure on firm productivity using the separation rate.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.166*** (0.002)	0.333*** (0.002)	0.337*** (0.002)
Human capital	0.668*** (0.022)	0.421*** (0.022)	0.279*** (0.022)
Years of operation	−0.009*** (0.000)	−0.007*** (0.000)	−0.008*** (0.000)
1998	−0.0134*** (0.005)	−0.105*** (0.005)	−0.105*** (0.005)
1999	−0.151*** (0.005)	−0.284*** (0.005)	−0.274*** (0.005)
2000	−0.152*** (0.006)	−0.315*** (0.006)	−0.291*** (0.006)
2001	−0.179*** (0.006)	−0.378*** (0.006)	−0.342*** (0.006)
2002	−0.331*** (0.007)	−0.548*** (0.007)	−0.505*** (0.007)
2003	−0.287*** (0.007)	−0.533*** (0.007)	−0.484*** (0.007)
2004	−0.330*** (0.007)	−0.589*** (0.007)	−0.531*** (0.007)
2005	−0.325*** (0.007)	−0.606*** (0.007)	−0.540*** (0.007)
2006	−0.319*** (0.007)	−0.615*** (0.007)	−0.541*** (0.007)
2007	−0.306*** (0.007)	−0.606*** (0.007)	−0.522*** (0.007)
2008	−0.283*** (0.008)	−0.601*** (0.008)	−0.510*** (0.008)
2009	−0.260*** (0.008)	−0.587*** (0.008)	−0.494*** (0.008)
2010	−0.221*** (0.008)	−0.541*** (0.008)	−0.437*** (0.008)
2011	−0.162*** (0.008)	−0.511*** (0.008)	−0.389*** (0.008)
2012	−0.123*** (0.008)	−0.486*** (0.008)	−0.349*** (0.008)
2013	−0.107*** (0.008)	−0.491*** (0.008)	−0.345*** (0.009)
Constant	6.468*** (0.038)	6.450*** (0.039)	6.645*** (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

In section 1.2.3, we mentioned two alternative ways to measure the human capital index of a firm. Thus far, all of the results have been based on one of these procedures. The aim of this subsection is to show whether the results are appropriate given this choice of variables. All of the results so far have been based on the index combining a complete secondary education with higher levels of education for the higher education dummy. The alternative

Table 9
Effect of learning on firm productivity using the turnover rate and alternative human capital measure.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.168*** (0.002)	0.341*** (0.002)	0.343*** (0.002)
Human capital (alternative)	0.688*** (0.023)	0.383*** (0.022)	0.218*** (0.022)
Years of operation	−0.009*** (0.000)	−0.008*** (0.000)	−0.009*** (0.000)
1998	−0.0207*** (0.004)	−0.127*** (0.004)	−0.130*** (0.004)
1999	−0.167*** (0.005)	−0.325*** (0.005)	−0.317*** (0.005)
2000	−0.166*** (0.006)	−0.350*** (0.006)	−0.327*** (0.006)
2001	−0.187*** (0.006)	−0.404*** (0.006)	−0.368*** (0.006)
2002	−0.339*** (0.007)	−0.576*** (0.007)	−0.534*** (0.007)
2003	−0.294*** (0.007)	−0.561*** (0.007)	−0.512*** (0.007)
2004	−0.337*** (0.007)	−0.620*** (0.007)	−0.560*** (0.007)
2005	−0.323*** (0.007)	−0.624*** (0.007)	−0.558*** (0.007)
2006	−0.313*** (0.007)	−0.635*** (0.007)	−0.561*** (0.007)
2007	−0.293*** (0.007)	−0.620*** (0.007)	−0.537*** (0.007)
2008	−0.268*** (0.007)	−0.612*** (0.007)	−0.524*** (0.007)
2009	−0.244*** (0.007)	−0.599*** (0.007)	−0.509*** (0.007)
2010	−0.207*** (0.007)	−0.561*** (0.007)	−0.461*** (0.007)
2011	−0.136*** (0.007)	−0.514*** (0.007)	−0.396*** (0.008)
2012	−0.093*** (0.008)	−0.488*** (0.008)	−0.354*** (0.008)
2013	−0.083*** (0.008)	−0.500*** (0.008)	−0.359*** (0.008)
Constant	6.479*** (0.036)	6.432*** (0.036)	6.667*** (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.

measure considers the complete secondary education level using a dummy representing an intermediary level of education. Tables 9 and 10 present results analogous to those shown in Tables 7 and 8 but using 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 10
Effect of learning on firm productivity using the separation rate and alternative human capital measure.

Variables	(1) OLS	(2) OLLEY-PAKES	(3) LEVINSOHN-PETRIN
Learning	0.163*** (0.002)	0.331*** (0.002)	0.336*** (0.002)
Human capital (alternative)	0.740*** (0.023)	0.491*** (0.022)	0.321*** (0.022)
Years of operation	−0.009*** (0.000)	−0.007*** (0.000)	−0.008*** (0.000)
1998	−0.013*** (0.005)	−0.105*** (0.005)	−0.105*** (0.005)
1999	−0.150*** (0.005)	−0.283*** (0.005)	−0.274*** (0.005)
2000	−0.149*** (0.006)	−0.313*** (0.006)	−0.290*** (0.006)
2001	−0.174*** (0.006)	−0.375*** (0.006)	−0.340*** (0.006)
2002	−0.323*** (0.007)	−0.543*** (0.007)	−0.502*** (0.007)
2003	−0.279*** (0.007)	−0.529*** (0.007)	−0.481*** (0.007)
2004	−0.318*** (0.007)	−0.582*** (0.007)	−0.526*** (0.007)
2005	−0.309*** (0.007)	−0.597*** (0.007)	−0.534*** (0.007)
2006	−0.299*** (0.007)	−0.604*** (0.007)	−0.533*** (0.007)
2007	−0.282*** (0.007)	−0.593*** (0.007)	−0.512*** (0.007)
2008	−0.255*** (0.007)	−0.585*** (0.007)	−0.499*** (0.007)
2009	−0.230*** (0.007)	−0.569*** (0.007)	−0.482*** (0.007)
2010	−0.187*** (0.007)	−0.521*** (0.007)	−0.424*** (0.007)
2011	−0.126*** (0.007)	−0.489*** (0.007)	−0.375*** (0.008)
2012	−0.084*** (0.008)	−0.464*** (0.008)	−0.333*** (0.008)
2013	−0.067*** (0.008)	−0.469*** (0.008)	−0.330*** (0.008)
Constant	6.470*** (0.037)	6.421*** (0.036)	6.631*** (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.

5. 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. First, the behavior of the turnover rate for the Brazilian formal job market in recent decades was described. The turnover rate has remained high and was indicated to be 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 with the learning variable, using an estimate of general human capital as a control. Thus, as a result, we obtained 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 has a negative impact, 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 the rates of job turnover and increasing the degree of negotiation between firms and employees.

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