Economics Bulletin

Volume 42, Issue 4

Manager education and firm productivity - evidence from Brazil

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Abstract

We merge two important Brazilian datasets (RAIS and PIA) to produce firm-level total factor productivity estimates that control for workers' human capital. Then we investigate the correlation between top managers' education and firms' TFP considering different levels of industry disaggregation. We find a positive, albeit small correlation for the industrial sector as a whole, and much higher correlations for some 2-digit industries. Also at the 2-digit level, we find that the positive correlation between firm TFP and manager schooling is lower for industries more dependent on external finance. Our results are robust to alternative, control function methods of TFP estimation, and to using different measures of manager education.

We would like to thank Glaucia Ferreira for her research assistance, and an anonymous referee for the useful comments made during the revision process. All possible errors are our own.
Citation: Eduardo C. De Souza and Marcelo R. Dos Santos and Vitor A.T. Fancio, (2022) "Manager education and firm productivity - evidence from Brazil", *Economics Bulletin*, Volume 42, Issue 4, pages 2298-2307
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Submitted: March 09, 2022. **Published:** December 30, 2022.

1 Introduction

The role of education in economic development is usually assessed in terms of aggregate human capital and labor productivity. Less attention is given to how managers' education impacts firms' productivity. As has been argued theoretically by Nelson and Phelps (1966) and Bloom et al. (2012), this is likely an important channel because managers are responsible for production technique, organizational and strategic decisions at the firm level. Recent literature, such as Queiró (2021) and Black (2019), brings empirical evidence on the relation between manager education/quality and firm productivity.

In this paper, we explore Brazilian microdata on several firm and employee characteristics. First, we estimate production function parameters and obtain firm-level total factor productivity (TFP) estimates. Then, we investigate the correlation between top managers' education and firms' TFP at different levels of industry disaggregation. Finally, we show that this correlation varies depending on the industry characteristics such as the R&D intensity and the dependence on external finance.

2 Data and productivity measurement

We rely on two datasets: the Annual Social Information Report (*Relação Anual de Informações Sociais - RAIS*) of the Ministry of Labor and Employment, and the Annual Industrial Survey (*Pesquisa Industrial Anual - PIA*) of the Brazilian Institute of Geography and Statistics. RAIS is an employer-employee dataset that covers the Brazilian formal labor market, including information on employee education, age, tenure and occupation.[1] PIA provides information on value-added, physical capital, and labor employment for Brazilian industrial firms. It covers all firms with 30 or more employees, and it randomly selects firms with 5 to 29 employees.

The merging of the two databases is possible because they share a common firm identifier, the *National Registry of Legal Entities (Cadastro Nacional de Pessoa Jurídica - CNPJ)*. Because every year there are some firms entering as well as other firms leaving the datasets, our sample is an unbalanced panel. It comprises on average 32,720 firms per year appearing in both RAIS and PIA between 1996 and 2017.

Different from other studies on Brazilian firms, such as Rocha et al. (2019) that estimate the TFP using only the physical capital and the number of workers as inputs, here we control for workers' human capital. Omitting this variable would produce a spurious correlation between manager human capital and firm TFP when (as seems reasonable) there exists a cross-firm positive correlation between workers' and managers' education.

We assume a Cobb Douglas production function $Y_{jt} = A_{jt} K_{jt}^{\alpha} H_{jt}^{\beta}$. The subscripts j and t indicate firm and time, respectively. Y_{jt} represents value-added, A_{jt} TFP, K_{jt} physical capital and H_{jt} total human capital for each firm. Total human capital is defined as $H_{jt} = h_{jt} L_{jt}$ where h_{jt} is the firm's average human capital and L_{jt} is the number of employees, including both workers and managers.

[1] RAIS follows a classification of occupations similar to ISCO 08. The information on employee occupation is particularly important for separating managers from other workers.

We use RAIS to compute the average human capital as

$$h_{jt} = \frac{\sum_{i \in j} h_{ijt}}{L_{jt}} \tag{1}$$

where $h_{ijt} = e^{\psi u_{ijt}}$ indicates the human capital of individual i in firm j at time t. u_{ijt} represents the number of schooling years. We set ψ to 0.13 according to Barbosa Filho and Pessôa (2008), who estimate returns to education in Brazil. We compute the value-added and physical capital using PIA data.

Next, separately for each industry[2] s , we estimate by LSDV

$$\ln Y_{jst} = \gamma_{0s} + \gamma_{1s} \ln K_{jst} + \gamma_{2s} \ln H_{jst} + \gamma_{3st} + \gamma_{4sj} + \varepsilon_{jst} \tag{2}$$

where γ_{3st} and γ_{4sj} are respectively time and firm fixed-effects.

The firm's TFP is then calculated as a Solow residual:

$$\ln TFP_{jst} = \ln Y_{jst} - \hat{\gamma}_{1s} \ln K_{jst} - \hat{\gamma}_{2s} (\ln h_{jst} + \ln L_{jst}) \tag{3}$$

where $\hat{\gamma}_{1s}$ and $\hat{\gamma}_{2s}$ are the sample estimates of the corresponding coefficients in (2).

Table 1 reports firm-level summary statistics of value-added and input factors.

Table 1: Summary statistics (production function)

Variable	Mean	Std. dev.	p5	p25	p50	p75	p95
Value-Added	28.17	830.07	0.14	0.81	2.18	7.24	64.87
Physical Capital	54.31	2093.26	0.15	0.78	2.75	11.45	114.83
Human capital	3.34	0.80	2.03	2.81	3.35	3.89	4.57
Years of Schooling	9.28	1.72	5.44	7.95	9.30	10.45	11.69
Labor	157.79	782.29	15	34	52	101	475

Notes: summary statistics for the whole universe of 114,234 firms that have yet appeared in both PIA and RAIS, regardless they have managers or not. Value-added and capital are in millions of 2017 Reais (the Brazilian currency), and labor corresponds to the total number of employees. Notes: Columns p5 to p95 report values for the firm located in the corresponding quantile.

In Figure 1, we set the TFP in 1996 equal to one and depict its evolution until 2017. The left panel shows the cross-firm average[3], and the right panel the quantiles. Notice that firms at the bottom of the TFP distribution *(p5)* are more volatile than firms at the top *(p95)*.

[2]The industry classification we use here is the version 2.0 of the *National Classification of Economic Activi-*

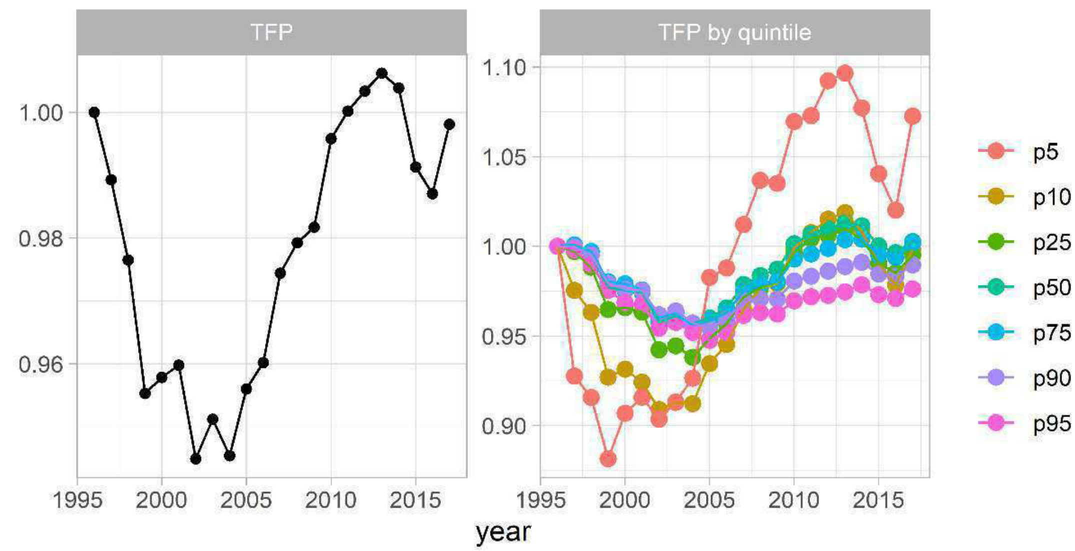

Figure 1: TFP evolution

3 Empirical strategy

Having estimated the firm's TFP, the next step is to identify in the data the top managers who presumably are responsible for decisions affecting the TFP. Here we consider as a top manager everyone in the firm who is a "director" according to RAIS and its underlying *Brazilian Classification of Occupations*. This leaves out all other managers, such as "production supervisors", "production managers", "sales managers", etc. With this top manager selection we cover 16,418 firms (that have one or more directors) in the 1996-2017 period.[4]

In line with this top manager selection, we define *hceo* as the average human capital of the directors in each firm-period:

$$hceo_{jt} = \frac{\sum_i m_{ijt} hceo_{ijt}}{\sum_i m_{ijt}} \quad \text{where} \quad m_{ijt} = \frac{\text{number of months director } i \text{ worked at firm } j \text{ in year } t}{12} \tag{4}$$

,where the individual director's human capital $hceo_{ijt}$ is computed using the years of schooling just as we did for workers in general (see the definition of h_{ijt} right below

ties (Classificação Nacional de Atividades Econômicas - CNAE) at the 2-digit disaggregation level, comprising 4 extractive and 25 manufacturing industries.

[3]It may seem counterintuitive that our average industrial firm's TFP displays a fall between 1996 and the early 2000s, when we recall that in this period the Brazilian economy underwent a significant liberalization process, including trade and deregulation reforms. However, a simultaneous fall in the Brazilian aggregate TFP has already been documented in the literature. See, for example, Cavalcanti Ferreira et al. (2013).

[4]This top manager selection provides a better coverage than the alternative of considering only single manager firms, with which we got only 9,667 firms in the 1996-2017 period. For reference, recall that we have on average 32,720 firms per year appearing in both RAIS and PIA between 1996 and 2017.

equation 1) .[5]

We are ready now for our "second stage regressions", where we regress firm productivity on top managers' human capital considering several specifications. The baseline is given by

$$\ln TFP_{jt} = \beta_0 + \beta_1 \ln hceo_{jt} + \beta_{2t} + \epsilon_{jt} \tag{5}$$

where TFP_{jt} is the TFP of firm j at period t estimated in (3). β_{2t} is a time fixed-effect.

Notice that we do not include in (5) a firm fixed-effect because, in view of how the TFP is estimated in (2) and (3), if we did so there would remain too little (namely, just random shocks) of the TFP for *hceo* to explain.

In the next two specifications, we control for other top manager characteristics:

$$\ln TFP_{jt} = \beta_0 + \beta_1 \ln hceo_{jt} + \beta_{2t} + \beta_3 \ln ten_{jt} + \epsilon_{jt} \tag{6}$$

$$\ln TFP_{jt} = \beta_0 + \beta_1 \ln hceo_{jt} + \beta_{2t} + \beta_3 age_{ceo_{jt}} + \beta_4 age^2_{ceo_{jt}} + \epsilon_{jt} \tag{7}$$

In (6) ten_{jt} is the average tenure of firm j's directors (with the tenure of each director measured as the accumulated number of months from his/her taking the job until the end of year t), and in (7) age_{jt} is the average age of firm j's directors.

Regressions (5), (6) and (7) are run in the pooling of all Brazilian industrial firms (as long as the firm has at least one director). We also estimate versions of these regressions using a finer 2-digit industry classification[6], so that (5), for example, becomes

$$\ln TFP_{jt} = \beta_0 + \{\beta_{1s}\}_{s=1}^{29} \ln hceo_{jt} + \beta_{2t} + \epsilon_{jt} \tag{8}$$

, where there are 29 2-digit industries.

Table 2 shows summary statistics for the variables appearing on regressions (5) to (8).[7] In order to make the relation between TFP and top managers' human capital immediately

[5] In our sample, the cross-firm correlation between h_j as defined in (1) and $hceo_j$ as defined in (4) is 0.52. As we argue in section 2 above, this positive correlation between workers' and managers' human capital is an important reason to control for workers' human capital when we measure the firm's TFP.

[6] Here we use the same industry classification as in (2) . See footnote 2.

[7] The only exception is the percentage of directors with a Bachelor's degree or more. This variable will be used later, in a robustness check.

apparent, all manager characteristics (except their mean and standard deviation) are displayed by the TFP quantile. In spite of a small variability[8], we notice that both *hceo* and the top managers' years of schooling are increasing in the TFP quantiles.

Table 2: Summary statistics (regressions)

Variable	Mean	Std. dev.	p5	p25	p50	p75	p95
TFP	6.86	1.48	4.60	6.24	6.96	7.67	8.85
Top managers' human capital (*hceo*)	6.33	1.49	6.18	6.12	6.25	6.29	6.47
Top managers' years of schooling	14.19	3.07	13.67	13.58	13.78	13.81	14.08
Top managers with Bachelor's degree or more (%)	71.92	41.03	66.67	66.74	70.31	71.68	78.37
Top managers' age	46.61	9.77	45.48	46.16	46.70	46.49	46.96
Top managers' tenure (in months)	94.90	86.97	82.88	93.23	100.61	98.57	92.81

Notes: Columns p5 to p95 report values for the firm located in the corresponding TFP quantile. "Years of schooling" is the within-firm cross-directors' average, which we add just for reference.

4 Results

4.1 Top manager education and firm TFP

In Table 3 we report the results from estimating specifications (5), (6) and (7). The main results are in the first panel, "TFP FE". There we find an elasticity of firm TFP with respect to manager human capital ranging from 9.37% to 12.70%.

Given the 0.13 value of the returns to education parameter ψ in $h_{ij} = e^{\psi u_{ij}}$, the 11.9% elasticity result in (5) is roughly equivalent to saying that the firm's TFP increases 1.5% per additional year of the average top manager's schooling.[9] This is considerably less than the 5% Portuguese corresponding figure in Queiró (2021).

However, when we inspect Table 2 we find that the cross-firm standard deviation in top managers' years of schooling is 3.07. So, if a firm were to increase its top managers' years of schooling in one standard deviation, it could achieve a 3.07 X 1.5% = 4.6% increase in its TFP, which is sizable.

Inspecting the columns for (6) and (7) in panel "TFP FE", we further find that the top managers' tenure and their age are positively correlated with the firm's TFP.

[8]Of course, when we observe manager characteristics by their own (not the TFP's) quantiles, there is much more variability. For years of schooling, for example, we have p5=10.21 (which corresponds to incomplete high school) and p95=15.35 (slightly above a Bachelor's degree).

[9]Equation (4) implies that $hceo_j$ is approximately equal to $e^{\psi u_{ceoj}}$, where u_{ceoj} is the top managers' average years of schooling for firm j. This, in turn, implies $dhceo_j/hceo_j = \psi du_{ceoj}$. On the other hand, in equation (5) we estimate an elasticity of the kind $\beta_1 = \dfrac{dTFP_j/TFP_j}{dhceo_j/hceo_j}$. Plugging in this equation the previous result for $dhceo_j/hceo_j$ yields $\beta_1 = \dfrac{dTFP_j/TFP_j}{\psi du_{ceoj}}$. Therefore, the semi-elasticity of TFP with respect to the top managers' average years of schooling is $\dfrac{dTFP_j/TFP_j}{du_{ceoj}} = \beta_1\ \psi$ = 11.9% X 0.13 = 1.5%.

Table 3: TFP X hceo - Regressions

	TFP FE			TFP ACFEST		
	(5)	(6)	(7)	(5)	(6)	(7)
Human capital$_{ceo}$	0.119***	0.127***	0.0937***	0.167***	0.167***	0.139***
Tenure$_{ceo}$		0.044***			0.0177*	
Age$_{ceo}$			0.0308***			0.0265***
Age$^2_{ceo}$			-0.0003***			-0.0003***
Constant	7.098***	6.930***	6.420***	5.630***	5.559***	5.107***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	No	No	No	No	No	No
Observations	92,055	92,055	92,055	83,021	82,985	83,021
Number of firms	16,418	16,418	16,418	14,526	14,522	14,526
*** p0.01, ** p0.05, * p0.1						

One objection that may be raised against our results is whether they are robust to alternative production function estimation methods. Truly, our naïve estimation in (2) did not return low and insignificant capital coefficients which, according to Collard-Wexler and De Loecker (2020), typically plague LSDV with firm fixed-effects.[10] However, there may be a component of the productivity shock ϵ_{jst} in (2) that is not observed by the econometrician but is observed by the firm, and to which the firm may adjust some of its inputs (such as the labor input). In this case, OLS estimates of the production function are biased and inconsistent, and our LSDV estimator may deal with the labor-productivity correlation but at the cost of imposing productivity shocks with no time variation.

To solve this problem, Olley and Pakes (2016), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) developed production function estimation methods based on "control functions", whereby investment or intermediate inputs flows serve as a proxy for the (unobserved by the econometrician but observed by the firm) productivity shocks.

In Table 3, panel "TFP ACFEST", we present our second stage regression results when the production function and the TFP are estimated by the Ackerberg et al. (2015) method, using the STATA program e-class command developed by Manjón and Mañez (2016), with intermediate inputs as the proxy variable.[11] There we see that we get elasticities of TFP with respect to *hceo* that are statistically significant and even higher than the ones we had obtained using our LSDV ("TFP FE") estimator.[12]

Are our second-stage results robust to alternative measures of top manager education?

[10]Indeed, when we estimate (2) we get statistical significance (at 1%) for γ_1 in 28 out of 29 2-digit industries. Furthermore, the cross-industry average of γ_1 is equal to 0.35, in line with standard values for the aggregate capital coefficient.

[11]Actually, we use the PIA's "cost of industrial operations" variable, which comprises intermediate materials plus consumption of energy and fuels.

[12]Not shown here, similar second-stage estimates obtain when we use the ACFEST estimator having the firm's investment in physical capital as the proxy variable.

In Table 4, instead of regressing the firm TFP on *hceo*, we regress it on the percentage of top managers with a Bachelor's degree or more. As suggested by the cross-TFP quantiles depicted in Table 2, this alternative measure of top manager education is also positively correlated with TFP.

Table 4: TFP X share of directors with bachelor's degree or more - Regressions

	TFP FE			TFP ACFEST		
	(5)	(6)	(7)	(5)	(6)	(7)
Share college$_{ceo}$	0.181***	0.183***	0.150***	0.130***	0.130***	0.107**
Tenure$_{ceo}$		0.0442***			0.0168*	
Age$_{ceo}$			0.0291***			0.0268***
Age$^2_{ceo}$			-0.0002***			-0.0003***
Constant	7.225***	7.068***	6.560***	5.848***	5.790***	5.293***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	No	No	No	No	No	No
Observations	92,151	92,020	92,058	83,107	82,986	83,022
Number of firms	16,432	16,415	16,418	14,542	14,522	14,526
*** p0.01, ** p0.05, * p0.1						

4.2 Industry heterogeneity and industry characteristics

Beneath the 0.119 elasticity of firm TFP with respect to top manager human capital that we found for the pooling of all Brazilian industrial firms in Table (3), there is considerable heterogeneity at the 2-digit industry level. When we estimate (8), we find a 1.15 elasticity for "miscellaneous products", 0.92 for "transport equipment" and for "printing and recording media", 0.759 for "Coke and petroleum", 0.694 for "metallic minerals", 0.52 for "pharmaceuticals", etc. But we also find some high negative elasticities: -1.438 for "computers and eletronic products", -1.262 for "oil and gas extraction" and -0.525 for "chemicals".[13]

How does the elasticity of firm TFP with respect to manager human capital relate to industry characteristics? In Figure 2 we take the coefficient associated to *hceo* from (8) and plot it against: i) the 2-digit industry's Herfindahl-Hirschman index; ii) the industry's Research and Development (R&D) intensity; and iii) the industry's dependence on external finance, as defined in Klapper et al. (2006) .[14]

[13] Out of 29 2-digit industries, we find 22 statistically significant (at 1%) elasticities, of which 13 are positive and 9 negative.

[14] We extract R&D intensities for the 2-digit industries from the Brazilian PINTEC, a survey on technology

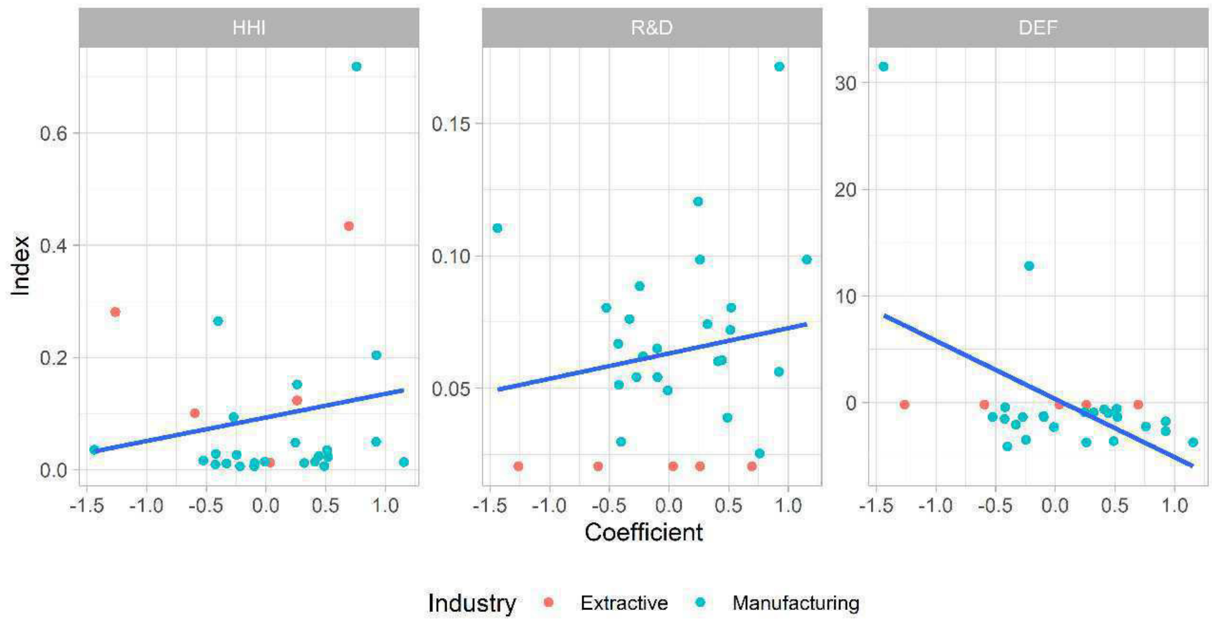

Figure 2: Correlations TFP-hceo coefficients X sector characteristics

The cross-industry correlation between the elasticity of firm TFP with respect to manager human capital and the Herfindahl-Hirschman index is only 0.16. The correlation between the TFP X *hceo* elasticity and the industry R&D intensity is 0.17. Neither correlation is statistically significant.[15]

For the dependence on external finance, we find a statistically significant -0.49 correlation with the elasticity of firm TFP with respect to manager human capital. The interpretation we give to this result is: in more credit constrained sectors, the connection between the firm's TFP and the managers' schooling is weaker. This pattern is rationalized by Castro and Ševčík (2017), in whose model credit frictions cause schooling investments to get misallocated: entrepreneurs with the best productivity potential are the ones compelled to reduce schooling investments the most. To our knowledge, we are the first to empirically document this pattern.

5 Conclusions

In this paper, we investigated the correlation between firm TFP and top manager education in the Brazilian industry. To do that, it was important to have a TFP measure that controls for workers' human capital, which we constructed merging the RAIS and PIA databases.

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and innovation. Klapper et al. (2006) define dependence of external finance as the ratio total investment expenditure/free cash flow, which we calculate from the Brazilian PIA and PINTEC.

[15]For the Portuguese industrial sector, Queiró (2021) finds that the positive correlation between firm TFP and manager schooling is higher for more R&D intensive industries. This evidence accords with the view that having more educated managers is important for firms' technology adoption.

At the 2-digit industry level, we found considerable heterogeneity in the size of the elasticity of firm TFP with respect to manager human capital. This elasticity is negatively correlated with the industry's dependence on external finance.

For the industrial sector as a whole, we estimated that the firm's TFP increases 1.5% per additional year of the top managers' schooling. The importance of this finding can be gauged when we consider long-run trends in education: Since the 90's, Brazil experienced a remarkable increase in school attainment. In our data, this is reflected in employees' years of schooling, whose average grew from 7.23 in 1996 to 10.39 in 2017. Compared to this, the growth in managers' years of schooling was much slower: from 13.63 to 14.51 in the same period. A back-of-the-envelope calculation using these figures together with our estimate suggests that the Brazilian industrial productivity could be 7.5% higher if the evolution in manager education had matched the evolution in workers' education.

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