Pontifícia Universidade Católica
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Daniel Veloso de Ávila Chaves

Industrial Policy and Self Selection: Assessing the Impact of the Informatics Law in Brazil

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Dissertation presented to the Programa de Pós-Graduação em Economia of the Departamento de Economia, PUC–Rio as partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Leonardo Bandeira Rezende

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Approved by the following commission:

Prof. Leonardo Bandeira Rezende
Advisor
Departmento de Economia — PUC–Rio

Prof. Gustavo Gonzaga
Departmento de Economia — PUC–Rio

Prof. Rafael Dix-Carneiro
Departamento de Economia — Duke

Prof. Monica Herz
Coordinator of the Centro de Ciências Sociais da PUC–Rio

Rio de Janeiro, June 12th, 2013

Daniel Veloso de Ávila Chaves

Graduated in Economics from the Universidade de Brasília in 2010.

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Abstract

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Technologically-oriented sectors in developing countries have been a common target for industrial policy. In this paper, we assess the effect of a government program that aims to foster productivity gains in the Brazilian computer industry (Informatics Law). A key feature of this program is the self-selection of firms. In order to obtain the correct estimates of productivity, we develop a production function estimation method that in addition to simultaneity and sample selection biases also takes into account the endogenous participation in the program. Our main results are: i) firms that choose to receive the benefit are on average less efficient and have a larger capital stock; ii) production function methods that do not take into account the self-selection in the program indicate that more (or equally) efficient firms are the ones choosing to receive the benefits and iii) productivity growth of firms that receive the benefit is higher than productivity growth of non-beneficiary firms.

Keywords

Informatics Law; Self Selection; Control Function; Productivity Growth; Brazil;

Resumo

Veloso, Daniel; Rezende, Leonardo B. (orientador). **Política Industrial e Auto-seleção: Avaliação dos Efeitos da Lei de Informática**. Rio de Janeiro, 2013. 55p. Dissertação de Mestrado — Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Neste artigo, nós estudamos o efeito da Lei de Informática sobre a produtividade da indústria brasileira de computadores. Um aspecto chave desta política é que a firma decide se quer ou não receber o benefício. Desta forma, para obter a medida correta de produtividade desenvolvemos um método de estimação de função de produção que além dos vieses de simultaneidade e seleção amostral leva em consideração a auto-seleção de firmas para receber o benefício governamental. Os nossos resultados são: i) firmas que escolhem receber o benefício do governo são em média menos produtivas e maiores, i.e, em média possuem maior estoque de capital; ii) métodos de estimação de função de produção que não consideram a auto-seleção de firmas na lei indicam que firmas mais (ou igualmente) produtivas adotam a lei e; iii) a taxa de crescimento da produtividade de firmas beneficiadas é maior que a das firmas que não recebem o benefício.

Palavras-chave

Lei da Informática; Auto-seleção; Função Controle; Produtividade; Brasil;

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I
Introduction

Over the last decades, technologically-oriented sectors in developing countries have been a common target for industrial policy. The evaluation of these government interventions requires measures of firm efficiency or productivity, which are difficult to obtain because they depend on the correct estimates of production function parameters.

In this paper, we assess the effect of government intervention through the Informatics Law in affecting productivity in the Brazilian computer industry. A key feature of this intervention is that participation was voluntary. If a firm chose to participate it would receive a tax exemption but as a counterpart it would have to invest in R&D and follow a local content requirement on inputs purchase. The fact that selection is not random and affects firm choice of inputs introduces an additional source of bias in the estimation of production function parameters. In order to obtain the correct estimates of production function parameters and productivity, we develop a structural method based on Olley and Pakes (1996), Levinsohn and Petrin (2003) and Doraszelski and Jaumandreu (2013).

Ribeiro et al. (2010) have estimated the effect of the policy by constructing a productivity measure based on the production function coefficients of the American computer industry and using a Differences-in-Differences estimator (DID). The main problem with their approach is the empirical strategy used to identify the policy effect. The DID estimator is suitable when there is an exogenous source of variation determining which firm will receive the benefit. However, the key feature of the Informatics Law is the fact that the firm chooses to be a participant of the program hence, the DID is not appropriate in this context. Moreover, an additional problem with their approach is that the American computer industry is not comparable to the Brazilian one. In fact, the Informatics Law by itself is a factor that differentiates both industries, thus being not clear if we can use the American coefficients in the Brazilian industry.

There is a vast literature concerning structural estimation of production function parameters. The seminal paper in this area is Olley and Pakes (1996). Using the dynamic problem of the firm and recognizing that the optimal investment rule is a monotone function of productivity, they suggest a method that controls for simultaneity between variable inputs and productivity and sample selection generated by the exit of firms. Levinsohn and Petrin (2003) point out the two major problems with the use of investment as a control function for unobserved productivity. First, they argue that due to adjustment costs the optimal investment might have kinks. In this case, investment may not respond to productivity shocks, hence the control for unobserved productivity will not be effective. The second point suggested by them is strictly data driven. Many firms report zero investment, therefore the approach suggested by Olley and Pakes (1996) will discard those observations of the sample.[1]

A common assumption in Olley and Pakes (1996) and Levinsohn and Petrin (2003) is that productivity evolves according to a first order exogenous Markov process. However, as is pointed out by De Loecker (2013), assuming a priori that productivity is exogenous to the firm and then trying to evaluate the effect over productivity of some policy that depends on firm compliance is incorrect.[2] First, the analysis will not be internally consistent - one should not assume that productivity is exogenous to the firm and then evaluate whether firm decisions affect productivity. Second, the estimated productivity measure is potentially incorrect; hence the analysis based on an incorrect measure will also be wrong.

In order to relax the exogenous productivity hypothesis, Doraszelski

[1] Note that in a context where reporting investment is not random, discarding observations with zero investment can bias the estimates.

[2] In De Loecker (2013) the main goal is to evaluate the hypothesis of learning by exporting.

and Jaumandreu (2013) build a model in which besides the investment in physical capital, the firm can also invest in R&D, which affect productivity. Their insights regarding the estimation of production function parameters is to recognize that in a context where R&D affects productivity, not necessarily the optimal investment rule will be invertible (monotone) on productivity. Thus, they use the known functional form of labor demand derived from profit maximization as a control function for unobserved firm productivity.

The structural method developed here builds on Olley and Pakes (1996), Levinsohn and Petrin (2003) and Doraszelski and Jaumandreu (2013) to recover the production function coefficients. In addition to accounting for the issues of simultaneity, sample selection and allowing productivity to be affected by law adoption, our method accounts for the effect of endogenous participation choice by individual firms into the Informatics Law.[3]

In our model the firm has to make three decisions: i) continue in the market or exit; ii) adopt the law or not; and iii) invest and demand variable inputs. Based on the insights of Levinsohn and Petrin (2003) and Doraszelski and Jaumandreu (2013) we use the known function of materials demand to control for unobserved productivity in a first stage regression that recovers the labor coefficient of the production function. The estimates of capital and materials coefficients are obtained on a second stage. We follow Olley and Pakes (1996) and use the law adoption and the continuation rules to control for both types of selection and recover the consistent materials and capital coefficients.

We apply our method to an unbalanced panel composed of 154 firms in the Brazilian Computer industry for the period of 2000 to 2009. The estimates of the production function parameters using our algorithm are compared to estimates obtained using OLS, Fixed Effects and two alternative approaches; one that controls for simultaneity between variable inputs and productivity (LP) and another that in addition to the simultaneity problem also controls for sample selection (OP).

Our labor coefficient estimates are lower than OLS and FE estimates

[3]We consider adoption as a reduced form; the real channel that adoption impacts productivity is through R&D investment.

but similar to LP and OP estimates. In the case of capital estimates, the theoretical model presented in this paper predicts that not controlling for sample and law adoption selection would generate a biased coefficient. Our estimator produces estimates that are higher than OLS, Fixed Effects and LP. On the other hand, the proposed method generates capital estimates that are lower than OP.

To analyze the determinants of self-selection into the Informatics Law, we compare productivity and capital densities and distributions between non-adopters and adopters before adoption. The analysis of sample selection is made by comparing productivity and capital densities between firms that stay in the sample for the whole period and firms that exit by 2009. The results are the following: i) Using incorrect measures of productivity obtained with OLS, FE, LP and OP indicate that adopters are selected from a pool of more (or equally) efficient firms.[4] On the other hand, using our measure of productivity reverses the selection pattern indicating that less efficient firms are the ones adopting the Informatics Law. ii) There is a positive relationship between participation in the Informatics Law and capital stock. iii) Survival firms have on average a larger capital stock than firms that exit by 2009 but there is no significant difference between the average productivity of these groups. With the industry aggregate productivity and aggregate productivity by firm status we find that despite the lower average productivity, adopters have a higher rate of productivity growth than non-adopters.

Our contributions with this paper are twofold. First, by introducing a method that allows two types of firm selection and endogenous productivity evolution we make a methodological contribution extending the previous literature related to the structural estimation of production function coefficients [Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerber et al. (2006) and Doraszelski and Jaumandreu (2013)]. The second contribution is related to policy analysis. We show that compared to OLS, FE, LP and OP productivity estimates, controlling for sample and Informatics Law

[4]FE productivity estimates indicates that adopters are more efficient. On the other hand, using OLS, LP and OP suggests that non-adopters and adopters are equally productive.

selection generates a reversion in the characteristics of productivity distribution indicating that adopters are on average less efficient than non-adopters. This result points out the importance of using the correct measure in policy analysis.

This paper is structured as follows: The next chapter presents the Brazilian computer industry institutional background. Information about the data is presented at chapter 3. At chapter 4 the firm decision model is presented. The fifth chapter presents the empirical framework. Chapter 6 provides the main results of our paper. This chapter presents the estimates of production function coefficients, an analysis of how capital and productivity are related to self-selection in the sample and in the Informatics Law and a discussion about relationship between Informatics Law and productivity growth . Chapter 7 discusses the policy implications of our results. Chapter 8 presents a robustness analysis of our estimates. Finally, chapter 9 concludes.

II
Institutional Background

The interest of the Brazilian government in stimulating the local computer industry started in the 1970's with the creation of a commission called *Comissão de Coordenação das Atividades de Processamento Eletrônico* (CAPRE). The major attribution of the CAPRE commission was to regulate imports of microcomputers. In order to increase intervention in the computer industry, the Brazilian government created in 1979 a new public agency to substitute the CAPRE commission. In addition to the original scope of the CAPRE commission, the new agency named *Secretaria Especial de Informática* (SEI), had a mandate to promote and regulate other high-tech industries as digital equipment, micro component and robotics.

During the 80's, the Brazilian government took a step further into the regulation of the computer industry. With the objective of developing a competitive national computer industry, Law 7232/1984 was enacted. The new legislation lasted for eight years and gave SEI the power to choose which firms could operate and discretion over establishing microcomputers importing quotas. Basically what the agency did was to restrict the national market to Brazilian firms and to promote an import substitution policy. A thorough study of the consequences of Law 7232/1984 on the Brazilian computer market is made by Luzio and Greenstein (1995).[1]

In the beginning of the 90's the government started the process of opening the Brazilian economy. Although extremely protectionist policies

[1]Luzio and Greenstein (1995) use a hedonic model to evaluate the performance of the Brazilian computer industry and compare it with international performance. They conclude that even with the rapid rate of advance in the national computer industry, the performance was far below the international potential.

were set aside, some benefits to the computer industry were kept in place under the new legislation, enacted in 1991 (Law 8248). The set of laws composed by Law 8248 and subsequent laws enacted in 2001 (Law 10176) and 2004 (Law 11077) will be called Informatics Law and is the focus of our analysis. Law 8248/1991 should have lasted until 2001 and its main purpose was to guarantee the development of the national computer industry and to foster productivity gains. Instead of letting Law 8248/1991 expire in 2001, the government took a few measures to postpone its validity. In 2001 Law 10176/2001 was enacted and its main consequence was to extend the validity of Law 8248/1991 until 2009. Finally, in 2004 a new amendment was passed (Law 11077/2004) and by now, the computer industry benefits program should last until 2019.

One important characteristic of the Informatics Law is that firm participation is voluntary and the benefit is given to a specific product. For example, it is possible to have a firm that produces three products - notebooks, PC's and printers - but demands the Informatics Law benefits only to the production of one good - printers. The trade-off faced by the firm is the following: If the firm decides to be a participant of the program, as a benefit it will have a tax cut of approximately 80% in the *Imposto sobre Produção Industrial* (IPI) over that specific product. On the other hand, the firm will be required to produce the benefited product following the *Processo Produtivo Básico* (PPB) imposed by the Ministry of Science and Technology which imposes to the firm the use of national content in the production of the final good. The firm is also required to invest 5% of its revenue in Research and Development (R&D).[2]

[2]In fact there are some specificities about the tax exemption and the R&D investment. In the most recent version - Law 11077/2004 - the tax exemption varies according to the region that the firm is placed and ranges from 80% to 95%. We also have that the tax exemption should be gradually reduced until 2019. Moreover, there are some rules of how the firm must must expend the 5% of the revenue devoted to R&D investment.

III
Data

The micro data related to production (revenue, labor, capital, materials, etc) are taken from *Pesquisa Industrial Anual* (PIA), a confidential database from the Brazilian Statistics Bureau (IBGE) and are the company accounts of firms operating in the manufacturing sector between 2000 and 2009 (more details on how the variables were constructed are given in appendix A). PIA is composed of two strata. The random stratum contains a sample of firms with the number of employees varying from 5 to 29. The deterministic stratum comprises all firms that have more than 30 employees and firms at the deterministic stratum must answer a more detailed questionnaire.

In the empirical analysis we will use a sample constructed with firms that have the mode of their industry classification across years equal to 30 (CNAE 30) and are at the deterministic stratum of PIA. Some firms report different classifications over time; we consider that a firm is in the computer industry if it reports the computer industry code in the majority of the years. We use only firms at the certain stratum because our empirical strategy requires variables that are reported only for firms at that stratum, e.g, the percentage of national inputs used by a firm.

The list of firms' and their products which are benefited by the Informatics Law is available at the Ministry of Science and Technology web site. Two problems with this list must be mentioned. First, the Ministry of Science and Technology started to release the names of the benefited firms and products only in 2001. So, by using this list we lose the information about firms that got the benefit during the 1990's. In order to mitigate this problem we did a research of which firms received the Informatics Law benefit in the period that goes from 1991 to 2000. Using a 1998 report released by the Ministry of Science and Technology we were able to track 10 firms that received the benefit until 1998. Although we were not able to track the firms that received the benefit in 1999 and 2000 we noticed that all firms that required the Informatics Law benefit until 1998 for some product also required the Informatics Law benefit for other products in the period that starts at 2001. Therefore, we have evidence to believe that the sample of firms that do not receive the benefits of the Informatics Law is not contaminated with firms that actually are receiving the Informatics Law benefits. The second problem is related to the structure of the database. PIA contains annual information on firm production; however this information is at the level of the firm and not at the level of each product that the firm produces. Therefore, in order to determine when the firm starts to receive the Informatics Law benefits we will have to choose a date based on one of their products. In this case, it is natural to define the law adoption date as the date when the firm first got the benefit for the first of its products.

We know from the Informatics Law setup that the decision to receive the benefit is up to the firm.[1] Table III.1 displays some information about the sample used in the empirical analysis and is informative about the sorting regarding this decision. The sample comprises a total of 561 observations through the ten years period. The average is of 56 observations per year with a minimum of 31 observations in 2000 and a maximum of 78 observations in 2008. We have a total of 25 firms adopting the law through the nine years period (we excluded the year 2000 from this calculation) with an average of approximately 3 firms adopting the law per year.

[1]We have not found any anecdotal evidence of government bureaucracy as a huge impediment of firms to require and receive the Informatics Law benefits.

Table III.1 – Number of Firms, Market-Share and Exit Rate by Status.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
# Observations	31	41	39	42	54	60	66	75	78	75
# non-adopters	21	27	22	25	36	42	43	51	54	55
# adopters	10	14	17	17	18	18	23	24	24	20
market-share of non-adopters (%)	62	47	42	15	21	23	35	30	20	23
market-share of adopters (%)	38	53	58	85	79	77	65	70	80	77
exit rate for non-adopters (%)	14	11	18	12	19	9	21	8	13	-
exit rate for adopters (%)	0	7	0	0	11	0	8	16	12	-

Source: IBGE/PIA, author's calculations.

One important point highlighted by table III.1 is that not all firms decide to receive the benefits and firms that receive it have a major participation in the market. The accumulated number of adopters varies from a minimum of 10 at the year 2000 from a maximum of 24 at years 2007 and 2008. We have per year that an average of 34% of the firms receive Informatics Law benefits and this set of firms have an average market-share of 70% . Even more interesting is that the exit rate of firms that receive the benefits is different from the exit rate of firms that do not receive the benefit. The average exit rate for firms that adopt the law is 6%. On the other hand, firms that do not adopt the law have an average exit rate of 14%.

Economic theory suggests that the decision of a firm to leave the market and the decision to adopt the law will depend on the expectation of the firm towards present and future profits. Therefore the difference between the exit rates of adopters and non-adopters associated with the fact that not all firms choose to receive benefits suggests that firms in these distinct groups face different incentives and are heterogeneous. Given our goal to estimate firm productivity in the computer industry, an empirical problem will arise if the heterogeneity in both groups of firms is not completely observed and is somehow related to firm profit maximization. In order to deal with the selection of firms in the adoption of the Informatics Law and the attrition generated by the exit of firms, a model of firm decision is presented in the next section.

IV
Behavioral Framework

Our ultimate empirical goal is to analyze the relationship between productivity and the Informatics Law in the Brazilian computer industry. In order to do so, the production function parameters must be correctly estimated: the estimation method must account for the selection bias generated by Informatics Law, the selection bias generated by firms exiting the market over time and the simultaneity problem between variable inputs and productivity.

We assume that every firm i in the market at period t operates with three inputs - capital (K_{it}); labor (L_{it}) and materials (M_{it}) - and that technology follows a Cobb-Douglas production function given by:

$$Y_{it} = exp[\omega_{it} + \epsilon_{it}]K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \quad (1)$$

where ω_{it} is firm productivity and ϵ_{it} is an independent random shock that the firm cannot forecast. Labor is demanded by firms in a competitive market and capital is a fixed input at period t. The demand for materials will depend on whether the firm adopts the law or not. Moreover, the decision to receive the Informatics Law benefit is permanent.

Adopters have a tax exemption; they do not have to pay the full amount of IPI tax.[1] On the other hand, they must invest 5% of their revenue in R&D (which can impact their productivity in the future), and must follow a local content requirement when purchasing materials. We model the net revenue gain of the IPI reduction and the expense in R&D through the output price: taking p^1 as the output price perceived by adopters and p^0 as the output price perceived by non-adopters we have that $p^1 > p^0$. To model the local content

[1] As it was defined in section 2, IPI is an acronym for *Imposto sobre Produção Industrial.* Basically, this is a tax over industrialized products.

requirement on materials purchase we assume that in the local market, price of materials is greater than price of materials in the international market. More specifically, taking $\tilde{p}_m$ as the price of materials in the local market and p_m as price of materials in the international market, $\tilde{p}_m > p_m$. One way to rationalize the intuition behind the difference in price of materials is to think that local materials market is smaller so supply has an upward sloping curve.[2]

Taking into account the net revenue gain, the fact that labor is demanded in a competitive market (firms take wages (w) as given) and the local content requirement, the static profit of an adopter given its capital stock is:

$$\tilde{\pi}_{it}^{law} = \max_{L_{it},M_{it}} p^1 exp[\omega_{it} + \epsilon_{it}]K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} - wL_{it} - \tilde{p}_m M_{it} \tag{2}$$

In the case of a non-adopter we do not have any tax exemption, R&D investment imposition or local content requirement in materials purchase. Thus, we assume that they take wages (w) and the price of materials (p_m) as given and receive p^0 for unity of output sold. The profit function of a non-adopter, given its capital stock is:

$$\tilde{\pi}_{it}^{Nlaw} = \max_{L_{it},M_{it}} p^0 exp[\omega_{it} + \epsilon_{it}]K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} - wL_{it} - p_m M_{it} \tag{3}$$

In order to make a decision the firm must consider not only the actual profits but also the discounted value of future profits. Productivity is known to the firm at the beginning of every period and is assumed to follow an endogenous Markov process which is affected by the decision of the firm to adopt or not the law. This captures the possibility of adoption affecting productivity in the long run through increased R&D investment. The capital stock of the firm evolves according to the accumulation equation given by:

[2] In a former version of this paper we actually modeled price of materials in the national market as an increasing function of total demand for materials in the national market. The problem with this approach is the difficulty to determine a closed functional form for the equilibrium demand for materials that we will use as proxy on the estimation algorithm.

$$K_{t+1} = (1-\delta)K_t + I_t \tag{4}$$

Consider the case of a firm that has already adopted the law in a previous year. At the beginning of a new period the firm has three decisions to make. First, the firm must decide if it continues in the market or leaves it. In case of exit, the firm earns a sell-off value Φ and never reappears again. If the firm decides to continue, it demands variable inputs in order to maximize the profit function given by equation (2) and invest.

At time period t the Bellman equation of a firm that has already adopted the Informatics Law is given by equation (5).

$$\begin{aligned} V_t^{law}(K_t,\omega_t) = \max\{\Phi, \sup_{I_t}\{\pi_t^{law}(K_t,\omega_t) - c(I_t) \\ + \beta \int V_{t+1}^{law}(K_{t+1},\omega_{t+1}) dP(\omega_{t+1}|\omega_t, law_t = 1)\}\} \end{aligned} \tag{5}$$

where $\pi_t^{law}(K_t,\omega_t)$ is the adopters profit as a function of productivity and capital, $c(I_t)$ is the cost of current investment and β is the firm's discount factor.[3] From equation (5) we can obtain an investment function and a continuation rule that is equal to 1 if the firm stays in the market and 0 otherwise. We write these functions respectively as:

$$i = \tilde{i}(\omega_t,\ K_t) \tag{6}$$

and

$$\tilde{\chi}_{it} = \begin{cases} 1 & \text{if } \omega_t \geq \tilde{\omega}_t^{cont}(K_t) \\ 0 & \text{if } \omega_t < \tilde{\omega}_t^{cont}(K_t) \end{cases} \tag{7}$$

One further point about the continuation rule should be noted. For simplicity, we assumed that the sell-off value is independent of K_t and ω_t. Since the continuation value function is increasing in K_t and ω_t (the profit

[3]From the foc's of equations (2) and (3) we obtain that the optimal demand for labor and materials depend on prices, productivity and capital. Therefore we can write the profit functions of adopters and non-adopters as functions of prices, productivity and capital. We also assume that at a given period t all adopters face the same net output price, wages and price of materials.

function is increasing in these variables) we will have a continuation rule with the cut-off form. However, note that even if the sell-off value depends on K_t and ω_t we still have a continuation rule with a cut-off form. In this case, all we need is that the difference between the continuation value and the sell-off value to be increasing in K_t and ω_t.

The chain of events to a firm that at the beginning of the period has not yet adopted the law is slightly different from a firm that in the past adopted the law. First, the firm decides if it stays in the market or if it leaves it. If the firm decides to exit, it receives a sell-off value Φ and never reappears again. If the firm decides to continue its operations, it must choose whether to adopt or not the incentive scheme of the Informatics Law. In case of adopting it, which is a permanent decision, the firm will have a profit function given by equation (2). On the other hand, if the firm decides not to follow the law incentive scheme, the profit function will be given by equation (3). After the decision to stay in the market and to adopt or not the law, the firm demands variable inputs and makes the investment. The Bellman equation of a firm in this case is given by equation (8).

$$\begin{aligned} V_t^{Nlaw}(K_t,\omega_t) = \max\{\Phi;\ \max\{\tilde{V}(K_t,\omega_t);\ \sup_{I_t}\{\pi_t^{Nlaw}(K_t,\omega_t) - c(I_t) \\ + \beta \int V_{t+1}^{N}(K_{t+1},\omega_{t+1})dP(\omega_{t+1}|\omega_t, law_t = 0)\}\}\} \end{aligned} \tag{8}$$

Where,

$$\begin{aligned} \tilde{V}(K_t,\omega_t) = \sup_{I_t}\{\pi_t^{law}(K_t,\omega_t) - c(I_t) \\ + \beta \int V_{t+1}^{law}(K_{t+1},\omega_{t+1})dP(\omega_{t+1}|\omega_t, law_t = 1)\} \end{aligned}$$

and $\pi_t^{nlaw}(K_t,\omega_t)$ is non-adopters profit as a function of capital and productivity, $c(I_t)$ is the cost of current investment and β is the firm's discount factor.[4] From equation (8) we obtain an investment function, a

[4]We also assume that at a given period t all non-adopters face the same output price,

continuation rule and a law adoption rule. The investment function is given by:

$$i = i(\omega_t,\ K_t) \tag{9}$$

As in the case of an adopter, the non-adopter continuation rule is equal to 1 if the firm continues its operations and zero otherwise. The continuation rule is given by:

$$\chi_{it} = \begin{cases} 1 & \text{if } \omega_t \geq \bar{\omega}_t^{cont}(K_t) \\ 0 & \text{if } \omega_t < \bar{\omega}_t^{cont}(K_t) \end{cases} \tag{10}$$

A priori, with the assumptions made so far we cannot make any statement about the form of the law adoption rule. Therefore, in order to guarantee that the law adoption rule have a cut-off form with only one threshold we will assume that the difference between $\pi_t^{nlaw}(K_t, \omega_t)$ and $\pi_t^{law}(K_t, \omega_t)$ is monotonic in ω. Proposition 1 gives the conditions over the parameters such that $\pi_t^{nlaw}(K_t, \omega_t) - \pi_t^{law}(K_t, \omega_t)$ is increasing or decreasing in ω_t.

Proposition 1 The difference between profits is generically monotone if and only if one of the following conditions hold:
(i) $\left(\frac{\tilde{p}_m}{p_m}\right)^{\beta_M} > \frac{p_1}{p_0}$
(ii) $\left(\frac{\tilde{p}_m}{p_m}\right)^{\beta_M} < \frac{p_1}{p_0}$

Proof: To simplify the notation, we will omit the indexes i and t. From the envelope theorem we have:

$$\frac{\partial \pi^{nlaw}}{\partial \omega}(L, M, K, \omega) = \frac{\partial f}{\partial \omega}(L^*_{nlaw}, M^*_{nlaw}, K, \omega)$$
$$\frac{\partial \pi^{law}}{\partial \omega}(L, M, K, \omega) = \frac{\partial f}{\partial \omega}(L^*_{law}, M^*_{law}, K, \omega)$$

wages and price of materials.

where * indicates the optimal demand for inputs and f is the production function. The difference between adopters and non-adopters profit will be decreasing or increasing in productivity if, and only if:

$$\frac{\partial \pi^{nlaw}}{\partial \omega}(L,M,K,\omega) > \frac{\partial \pi^{law}}{\partial \omega}(L,M,K,\omega) \quad \forall \omega \tag{11}$$

or

$$\frac{\partial \pi^{nlaw}}{\partial \omega}(L,M,K,\omega) < \frac{\partial \pi^{law}}{\partial \omega}(L,M,K,\omega) \quad \forall \omega \tag{12}$$

From equation (11), the envelope theorem and the fact that the production is a Cobb-Douglas $\pi_t^{nlaw}(K_t,\omega_t) - \pi_t^{law}(K_t,\omega_t)$ is increasing in ω if and only if:

$$p^0 K^{\beta_K} (L^*_{nlaw})^{\beta_L} (M^*_{nlaw})^{\beta_M} > p^1 K^{\beta_K} (L^*_{law})^{\beta_L} (M^*_{law})^{\beta_M} \Leftrightarrow$$

$$\left(\frac{L^*_{nlaw}}{L^*_{law}}\right)^{\beta_L} \left(\frac{M^*_{nlaw}}{M^*_{law}}\right)^{\beta_M} > \frac{p^1}{p^0} \tag{13}$$

From equation (12), the envelope theorem and the fact that the production is a Cobb-Douglas $\pi_t^{nlaw}(K_t,\omega_t) - \pi_t^{law}(K_t,\omega_t)$ is decreasing in ω if and only if:

$$p^0 K^{\beta_K} (L^*_{nlaw})^{\beta_L} (M^*_{nlaw})^{\beta_M} < p^1 K^{\beta_K} (L^*_{law})^{\beta_L} (M^*_{law})^{\beta_M} \Leftrightarrow$$

$$\left(\frac{L^*_{nlaw}}{L^*_{law}}\right)^{\beta_L} \left(\frac{M^*_{nlaw}}{M^*_{law}}\right)^{\beta_M} < \frac{p^1}{p^0} \tag{14}$$

Since for every i and t we have a regular profit maximization with a Cobb-Douglas production function and firms take prices as given according to their status we have that the optimal demand for labor and materials can be written as:

$$L^*_j = KA^{\frac{1}{1-\beta_L-\beta_M}} \left(\frac{p^j \beta_L}{w}\right)^{\frac{1-\beta_M}{1-\beta_L-\beta_M}} \left(\frac{p^j \beta_M}{p^j_m}\right)^{\frac{\beta_M}{1-\beta_L-\beta_M}} \tag{15}$$

$$M^*_j = KA^{\frac{1}{1-\beta_L-\beta_M}} \left(\frac{p^j \beta_L}{w}\right)^{\frac{\beta_L}{1-\beta_L-\beta_M}} \left(\frac{p^j \beta_M}{p^j_m}\right)^{\frac{1-\beta_L}{1-\beta_L-\beta_M}} \tag{16}$$

where j index the firm status and $A = exp[\omega + \epsilon]$. Applying equations (15) and (16) to equation (13) we obtain that $\pi_t^{nlaw}(K_t, \omega_t) - \pi_t^{law}(K_t, \omega_t)$ is increasing in ω if and only if:

$$\left(\frac{\tilde{p}_m}{p_m}\right)^{\beta_M} > \frac{p_1}{p_0} \tag{17}$$

Moreover, applying equations (15) and (16) to equation (14) we obtain that $\pi_t^{nlaw}(K_t, \omega_t) - \pi_t^{law}(K_t, \omega_t)$ is decreasing in ω if and only if:

$$\left(\frac{\tilde{p}_m}{p_m}\right)^{\beta_M} < \frac{p_1}{p_0} \tag{18}$$

Thus, the law adoption rule is given by:

$$\Upsilon_t = \begin{cases} 1 & \text{if } \omega_t < \bar{\omega}_t^{law}(k_t) \text{or } \ \omega_t > \bar{\omega}_t^{law}(k_t) \\ 0 & \text{if } \omega_t \geq \bar{\omega}_t^{law}(k_t) \text{or } \ \omega_t \leq \bar{\omega}_t^{law}(k_t) \end{cases} \tag{19}$$

Analyzing the continuation rule we can make predictions about the self-selection generated by firms exiting the market. Consider the continuation rules in equation (7) and (10). From the fact that the value function must be increasing in the capital stock (the profit function is increasing in capital) we have that the continuation cut-offs must be a decreasing function of capital. Therefore, firms with a larger capital stock can expect a larger return for any productivity realization. Hence, we would expect that firms that stay in the market for the whole period have on average a greater capital stock.

Predictions about law adoption are not straightforward. The first problem is that we do not know exactly how the law adoption cut-off works, i.e, we do not know if we have the selection of more productive or less productive firms to receive the Informatics Law benefits. Moreover, even if we knew how the cut-off rule works, in order to predict the selection to receive Informatics Law benefits we must consider law adoption and continuation cut-offs (the law adoption is conditional on the firm staying in the market). As an example, assume that the law adoption cut-off is also a decreasing function of capital. In this case, if law adoption cut-off is a steeper function of capital than the continuation cut-off, we would expect firms with lower capital stock adopting the law. On the other hand, if the continuation cut-off is a steeper function of capital than the law adoption cut-off, we would have the opposite; firms with higher capital stock would be the ones adopting the law.

V
Empirical Framework

From the hypothesis that firms produce according to a Cobb-Douglas function with three inputs - capital, labor and materials - we have the following equation to estimate:

$$y_{it} = \beta_L l_{it} + \beta_M m_{it} + \beta_K k_{it} + \omega_{it} + \epsilon_{it} \tag{1}$$

where y_{it} is the log of revenue from firm i at period t, l_{it} is the log of its labor inputs, m_{it} is the log of its materials inputs, k_{it} is the log of its capital inputs, ω_{it} its productivity and ϵ_{it} is an independent shock to productivity which cannot be forecasted by the firm in the period that it can adjust labor and materials.

Unfortunately ω_{it} is not observed by the econometrician. Thus, the first problem of estimating equation (1) by OLS concerns the endogeneity between variable inputs and productivity. From the timing of the model we know that a firm demands labor after observing realized productivity. From the optimal labor demand, we know that there is a positive relationship between labor and productivity so, as is pointed out by Marschak and Andrews (1944), we would expect a positive bias in OLS labor estimates.

Now let's evaluate the other two possible sources of bias in the estimation of equation (1). As suggested by Olley and Pakes (1996) and by the previous discussion, we must take into account the problem of firm selection generated by the exit of firms through time and by law adoption. First, consider the case where we only control for the selection generated by the exit of firms. We can write ω_{t+1} as:

$$\omega_{it+1} = E[\omega_{t+1}|\omega_t,\ law_t,\ \chi_{t+1} = 1] + \tilde{\xi}_{t+1} \tag{2}$$

Substituting (2) into equation (1) (evaluating at $t+1$) we would have at the right side the term given by the expression: $E[\omega_{t+1}|\omega_t,\ law_t,\ \chi_{t+1}=1]$. From the model discussion we know that the continuation cut-off is a decreasing function of capital. Thus, the self selection generated by the exit of firms implies that $E[\omega_{t+1}|\omega_t,\ law_t,\ \chi_{t+1}=1]$ is decreasing with k, generating a negative bias in the capital coefficient. Moreover, note that the term $\tilde{\xi}_{t+1}$ in equation (2) still carries information concerning the adoption of the law at $t+1$. From the decision rule given by equation (19), the decision of adoption is a function of firm capital. Therefore, even if the estimation procedure takes into account the expectation term given at equation (2), omitting the selection of firms into the Informatics Law will generate biased capital coefficient estimates.

In order to consider the selection generated by the exit of firms through time and by law adoption, we should write ω_{t+1} as:

$$\omega_{t+1} = E[\omega_{t+1}|\omega_t,\ law_t,\ \chi_{t+1}=1,\ law_{it+1}] + \xi_{t+1} \tag{3}$$

Proceeding as before and substituting equation (3) into equation (1) (evaluating at $t+1$) we would have at the right side the term given by the expression: $E[\omega_{t+1}|\omega_t,\ law_t,\ \chi_{t+1}=1,\ law_{t+1}]$. Note that in this case the term ξ_{t+1} carries no information about the decision do adopt the law or to stay in the market.[1] Thus if we can control for the expectation term at equation (3) we will be able to recover the consistent estimates of the production function coefficients.

The estimation algorithm consists of two separate stages. In the first stage we obtain the labor coefficient and in the second stage we estimate materials and capital coefficients. Labor and materials are considered variable inputs, capital is a fixed factor and it is determined by firm investment made in the previous year.[2] As in Levinsohn and Petrin (2003), we will estimate the labor coefficient using the demand for materials as a control function for the unobserved productivity. The main advantage of relying on an approach

[1]It is important to point out that since we cannot state a-priori the relationship between capital and law adoption, it is not possible to define the direction of the bias in the capital coefficient.

[2]The optimal investment decision is given by equations (6) and (9).

based on Levinsohn and Petrin (2003) instead of an approach based on Olley and Pakes (1996) is that as is pointed out by Doraszelski and Jaumandreu (2013) with an endogenous Markov process nothing guarantees that the investment function will be invertible, i.e, investment is not necessarily a proxy for productivity. The starting point is to recognize that demand for materials m_{it} is directly related to firm's productivity level, capital stock and with their decision to receive or not the Informatics Law benefits. This gives rise to the following demand for materials:

$$m_{it} = m_t(k_{it}, \omega_{it}, law_{it}) \tag{4}$$

Using the fact that profits are given by equations (2) and (3) and from profit maximization at every period t we will have that demand for materials is monotonically increasing in productivity. Therefore, we can rely on the following equation to proxy unobserved productivity:

$$\omega_{it} = h_t(k_{it}, m_{it}, law_{it}) \tag{5}$$

Substituting equation (5) into (1) we obtain:

$$y_{it} = \beta_L l_{it} + \underbrace{\beta_M m_{it} + \beta_K k_{it} + h_t(k_{it}, m_{it}, law_{it})}_{=\phi_{it}} + \epsilon_{it} \tag{6}$$

We identify the labor coefficient by applying the OLS estimator to equation (6) and by approximating the function h_t with a third degree polynomial function that considers capital, materials and the interaction of these variables with law adoption dummy and year dummies. The inclusion of these dummy variables is important because one crucial assumption to identify the labor coefficient is that input and output prices are the same within the group of adopters and within the group of non-adopters. In addition to $\hat{\beta}_L$, at the first stage of our estimation procedure we also obtain an estimate of $\hat{\phi}_{it}$ that will be used at the second stage of the estimation algorithm. Moreover, one important feature of our approach is the difference between materials demand of adopters and non-adopters. This difference helps to mitigate the problem of collinearity between labor and materials that is present in Levinsohn and Petrin (2003). [3]

[3]To a thorough discussion, see Ackerberg et al. (2003).

Consider the identification of the coefficients β_K and β_M in the second stage. Substitute equation (3) in equation (1) to obtain:

$$\begin{aligned} y_{it+1} = {} & \beta_L l_{it+1} + \beta_M m_{it+1} + \beta_K k_{it+1} + E[\omega_{t+1}|\omega_t,\, law_t,\, law_{t+1},\, \chi_{t+1} = 1] \\ & + \xi_{t+1} + \epsilon_{t+1} \end{aligned} \tag{7}$$

The expectation term can be written as:

$$E[\omega_{t+1}|\omega_t,\, law_t,\, law_{t+1},\, \chi_{t+1} = 1] = \begin{cases} \tilde{g}_1(\omega_t,\, \bar{\omega}^{law}_{t+1}(k_{t+1}),\, \bar{\omega}^{cont}_{t+1}(k_{t+1})) & law_{it} = 0 \\ \tilde{g}_2(\omega_t,\, \tilde{\omega}^{cont}_{t+1}(k_{t+1})) & law_{it} = 1 \end{cases} \tag{8}$$

The problem with equation (8) is that we do not have the continuation and law adoption cut-offs. To proceed, we will show that we can write them as a function of survival and law adoption probabilities. The survival probability at $t+1$ of a firm that until t has not adopted the law is written as:

$$\begin{aligned} P \equiv Pr[\omega_{t+1} \geq \bar{\omega}^{cont}_{t+1}(k_{t+1}) | \bar{\omega}^{cont}_{t+1}(k_{t+1}),\, \omega_t] \\ = \varphi_t(\bar{\omega}^{cont}_{t+1}(k_{t+1}),\, \omega_t) \\ = \tilde{\varphi}_t(i_t,\, k_t,\, m_t) \end{aligned} \tag{9}$$

In the case of a firm that has already adopted the law, the probability of survival at $t+1$ is:

$$\begin{aligned} \tilde{P} \equiv Pr[\omega_{t+1} \geq \tilde{\omega}^{cont}_{t+1}(k_{t+1}) | \tilde{\omega}^{cont}_{t+1}(k_{t+1}),\, \omega_t] \\ = \tau_t(\tilde{\omega}^{cont}_{t+1}(k_{t+1}),\, \omega_t) \\ = \tilde{\tau}_t(i_t,\, k_t,\, m_t) \end{aligned} \tag{10}$$

The probability of law adoption can be written as:

$$Q \equiv Pr[\bar{\omega}_{t+1}^{cont}(k_{t+1}) < \omega_{t+1} < \bar{\omega}_{t+1}^{law}(k_{t+1}) | \bar{\omega}_{t+1}^{cont}(k_{t+1}),\ \bar{\omega}_{t+1}^{law}(k_{t+1}),\ \omega_t] \tag{11}$$
$$= \psi(\bar{\omega}_{t+1}^{cont}(k_{t+1}),\ \bar{\omega}_{t+1}^{law}(k_{t+1}),\ \omega_t)$$
$$= \tilde{\psi}(i_t,\ k_t, m_t)$$

It is important to point out that the second equality in equations (9), (10) and (11) follows from the relationship between productivity and materials demand and from the capital accumulation equation. Using Olley and Pakes (1996) insights, equations (9) and (10) can be inverted, so the continuation cut-offs can be expressed as a function of survival probabilities.[4] The same procedure can be applied to the law adoption probability, but in this case we will write the law adoption cut-off as a function of the law adoption probability and the continuation cut-off. Applying equation (8) to equation (1) and expressing the cut-offs as functions of probabilities we have:

$$\begin{aligned} y_{it+1} = \beta_L l_{it+1} + \beta_M m_{it+1} + \beta_K k_{it+1} + (1 - law_{it}) \times \tilde{\tilde{g}}_1(\omega_t,\ Q,\ P) \\ + law_{it} \times \tilde{\tilde{g}}_2(\omega_t,\ \tilde{P}) + \xi_{t+1} + \epsilon_{t+1} \end{aligned} \tag{12}$$

From the first stage, productivity is known up to parameters, $\omega_{it} = \hat{\phi}_{it} - \beta_M m_{it} - \beta_K k_{it}$, and we also have the estimates of the labor coefficient $(\hat{\beta}_L)$. Moreover, the probabilities P, $\tilde{P}$ and Q can be estimated using probit models. Therefore, equation (12) becomes:

$$y_{it+1} - \hat{\beta}_L l_{it+1} = \beta_M m_{it+1} + \beta_K k_{it+1} + (1 - law_{it}) \times \tilde{\tilde{g}}_1(\hat{\phi}_{it} - \beta_M m_{it} - \beta_K k_{it}, \hat{Q}, \hat{P})$$
$$+ law_{it} \times \tilde{\tilde{g}}_2(\hat{\phi}_{it} - \beta_M m_{it} - \beta_K k_{it},\ \hat{\tilde{P}}) + \hat{\xi}_{t+1} + \hat{\epsilon}_{t+1} \tag{13}$$

where we can approximate the functions $\tilde{\tilde{g}}_1(\hat{\phi}_{it} - \beta_M m_{it} - \beta_K k_{it},\ \hat{Q},\ \hat{P})$ and $\tilde{\tilde{g}}_2(\hat{\phi}_{it} - \beta_M m_{it} - \beta_K k_{it},\ \hat{\tilde{P}})$ by third degree polynomial functions.

[4]Provided the density of ω_{t+1} conditional on ω_t is positive in the region of the cut-off.

Following the approach used in Levinsohn and Petrin (2003), Doraszelski and Jaumandreu (2013) and De Loecker (2011), the capital and materials coefficients in equation (13) are estimated using the sample analogues of the following moment conditions.

$$E[(\xi_{t+1} + \epsilon_{t+1}) \times k_{it+1}] = 0 \tag{14}$$

$$E[(\xi_{t+1} + \epsilon_{t+1}) \times m_{it}] = 0 \tag{15}$$

VI
Results

In this section we present the results of our approach and compare them with a few benchmark estimates. We show the importance of controlling for the Informatics Law and survival self-selection. With production function estimates, we recover a measure of firm productivity. We relate productivity and capital to the decision to receive the law benefits and to stay in the market. More specifically, we make the comparison of these variables between non-adopters and adopters before adoption and between survivors and firms that exit by 2009. Moreover, we construct a measure of aggregate productivity and explore the link between the Informatics Law and productivity growth at the industry.

VI.1 Production Function Coefficients and Productivity Estimates

The results of the proposed estimation procedure together with other alternative estimates of the production function coefficients are provided in table VI.1. Column 1 provides Least Square estimates (OLS); column 2 provides the estimates of the production function coefficients using a Fixed Effects estimator (FE).[1] Column 3 provides estimates obtained controlling only for simultaneity between variable inputs and productivity as in Levinsohn and Petrin (2003) (LP). Column 4 displays estimates controlling for simultaneity and sample selection as in Olley and Pakes (1996) (OP). Finally, Column 5 provides estimates of the production function based on the

[1]A model which uses fixed effects of firm.

method proposed here (Main).[2]

We report different sample sizes in the estimates at columns (4) and (5). It happens that in the estimation of production function using OP we need to use firm investment in the control function. Hence, we lose observations with zero investment. Moreover, there are two reasons for the reduced sample in the second step of the Main approach: i) we lose observations in order to implement the GMM estimator (one of the instruments is the lagged materials) and ii) the survival and law adoptions probabilities are estimated as a function of firm investment and not all firms report investment in all periods.

Table VI.1 – Alternative Estimates of Production Function Parameters

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	LP	OP	Main
Labor	0.119	0.297	0.055	0.026	0.053
	(0.047)	(0.065)	(0.047)	(0.049)	(0.047)
Capital	0.150	0.0556	0.090	0.275	0.260
	(0.0294)	(0.032)	(0.0948)	(0.105)	(0.127)
Materials	0.572	0.353	0.760	0.573	0.766
	(0.0353)	(0.0635)	(0.2599)	(0.039)	(0.307)
N	561	561	561	464	561/285
Returns to Scale	0.841	0.7056	0.905	0.874	1.079
P values*	0.000	0.0031	0.682	0.231	0.824
Year dummies	yes	yes	yes	yes	yes

Standard erros in parentheses are calculated considering firm clusters.

* P values of constant returns to scale test.

The first point to note is that the labor coefficient decreases when we compare LP, OP and Main estimates, 0.055, 0.026 and 0.053 respectively, with OLS and FE estimates: 0.119 and 0.297 respectively. The decrease in labor coefficient when we control for unobserved productivity is the usual

[2]The estimates presented at columns 3 and 4 are obtained with the levpet and opreg Stata programs.

results in the literature (Marschak and Andrews (1944) and Griliches and Mairesse (1995)). We should also note that even though LP, OP and Main labor estimates are lower than OLS and FE they are not significant.

Consider the estimation of the second stage, i.e, of capital and materials coefficients. As was discussed in the previous section, if both selections were ignored, the estimated equation would suffer from omitted variable bias. However, we are not able to specify the signal of the bias.[3] The capital coefficient estimates using OLS, FE and LP are 0.150, 0.0556 and 0.09 respectively. On the other hand, controlling for the possible selection into the sample and into the law (Main) generates capital coefficient estimates of 0.26. Moreover, when we correct only for the sample selection bias (column 4 - OP), the capital coefficient estimate increases, going in the direction predicted by the literature.

Until now, we have focused on the bias correction generated by the method proposed. Another related point concerns the estimated returns to scale. The estimated returns to scale obtained by each method and the p-values of a constant returns to scale test are displayed at table VI.1. As we can see, OLS and FE generate estimates that suggest decreasing returns to scale. LP and OP also generate estimates that are smaller than one. However, we cannot reject the hypothesis that the returns to scale generated by these methods are constant. Furthermore, our approach generates the estimates closer to one and we cannot reject the hypothesis of constant returns to scale. This is an additional evidence that the proposed method is more accurate than traditional methods to estimate the parameters of the production function for the Brazilian Computer industry.

An essential input to the analysis of the Informatics Law is a measure of firm productivity. Using the coefficient estimates $\hat{\beta}_L$, $\hat{\beta}_M$ and $\hat{\beta}_K$ at table VI.1, we compute productivity according to the following expression: $\hat{\omega}_{it} = y_{it} - \hat{\beta}_L l_{it} - \hat{\beta}_M m_{it} - \hat{\beta}_K k_{it}$.

[3]In a context similar to Olley and Pakes (1996) where we only have the selection generated by firms exiting the market, we would expect a negative bias in the capital coefficient.

VI.2 Determinants of Adoption

Capital and productivity are two key factors in explaining self-selection in the Informatics Law. Table VI.2 and figure VI.1 display the results of a difference in means test between the stock of capital of adopters and non-adopters and density estimates of the distribution of capital for both groups. As we can see, there is strong evidence that adopters are on average larger than non-adopters (taking capital stock as the measure of size).

Table VI.2 – Capital Mean Test by Firm Status

	Non-Adopters	Adopters	Δ	t statistics
Capital	13.458	14.675	-1.217	-2.97
	(0.120)	(0.347)	(0.409)	
# Obs.	344	32		

Standard Errors in Parentheses.

Figure VI.1 – Capital Kernel Density Estimate - Adopters vs. Non-Adopters

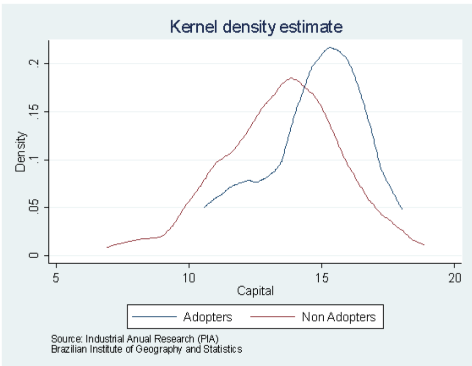


Table VI.3 displays the difference of means test for productivity between adopters and non-adopters. We have that productivity estimates recovered using OLS, LP and OP indicate that there is no difference between average productivity of adopters and non-adopters. In the case of FE estimates, we find that adopters are on average more efficient than non-adopters. On the other hand, when we make the comparison using Main productivity estimates we find that adopters are on average less productive than non-adopters.

Table VI.3 – Difference of Mean Test for Productivity by Firm Status

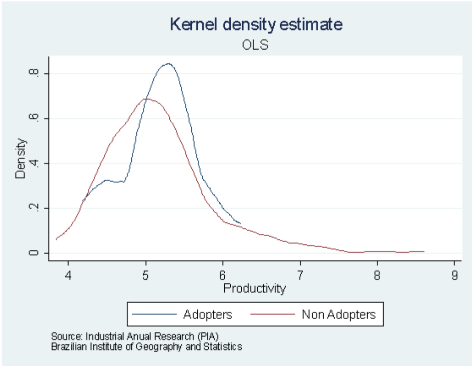
Estimation Method	Non-Adopters	Adopters	Δ	t statistics
OLS	5.152	5.161	-0.009	-0.072
	(0.037)	(0.091)	(0.124)	
Fixed Effects	9.145	9.388	-0.242	-1.630
	(0.0439)	(0.1193)	(0.1486)	
LP	3.295	3.192	0.1028	0.744
	(0.041)	(0.0975)	(0.1383)	
OP	3.778	3.720	0.057	0.427
	(0.040)	(0.098)	(0.135)	
Main	0.900	0.582	0.317	1.991
	(0.048)	(0.103)	(0.159)	
# Obs.	344	32		

Standard Errors in Parentheses.

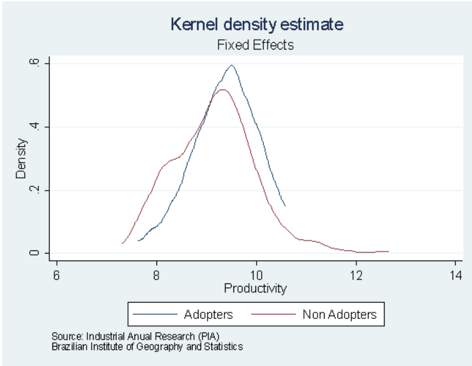
In addition to the mean comparison test, we make a graphical comparison of the density function for each group and the Kolmogorov-Smirnov test for equality between productivity distributions. Figure VI.2 displays the estimated productivity density of adopters and non-adopters using OLS, FE, LP, OP and Main productivity estimates. As we can see, using OLS, LP and OP productivity estimates generate density functions for adopters and non-adopters that are similar to each other. Considering productivity densities obtained with FE, we have that the shapes of the densities are similar but, as is predicted by the mean comparison test, productivity density of adopters is shifted to the right. On the other hand, when we consider productivity densities obtained with Main estimator we find that both densities have a similar shape but the density of non-adopters is shifted to the right compared to the density of adopters.

Figure VI.2 – Productivity Kernel Density Estimates - Adopters vs. Non-Adopters

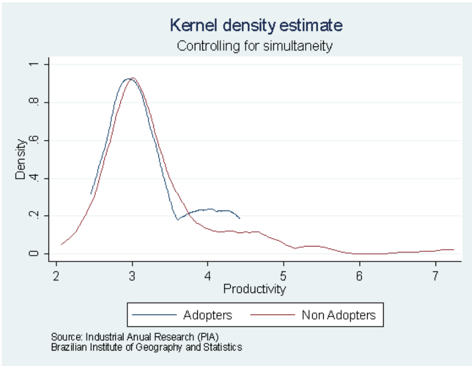
(VI.2(a)) OLS



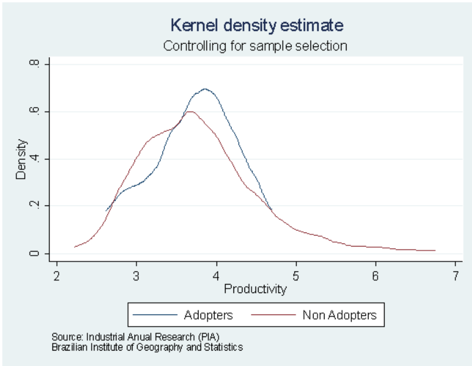
(VI.2(b)) FE



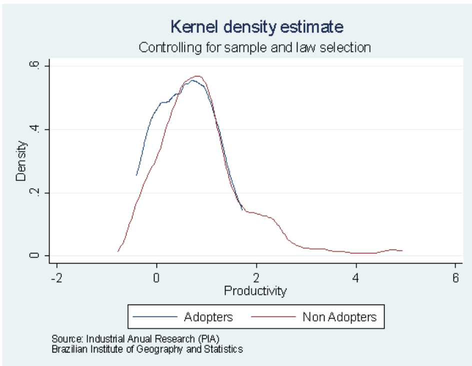
(VI.2(c)) LP



(VI.2(d)) OP



(VI.2(e)) Main



The graphical analysis and the mean comparison test point out to the difference between productivity distribution of adopters and non-adopters. In order to confirm this result, we follow Doraszelski and Jaumandreu (2013) and Delgado et al. (2002), and apply a two and one sided Kolmogorov-Smirnov test. Since this test requires the observations in each sample to be independent we cannot apply it direct to the measure of firm productivity. To solve this problem we use as the variable of interest the average firm productivity. In case of adopters, we average only over the years prior the law adoption.

The results of the two sided test are displayed in table VI.4 columns 1 and 2. Columns 3 and 4 display the results of the one sided test. Considering the two sided test, we reject the null hypothesis that both distributions are equal in all cases with the exception of LP. In addition to test whether distributions are different between groups of firms, we can use the one sided test to check if the distribution of adopters stochastically dominates the distribution of non-adopters. As we can see from columns 3 and 4, when we use OLS, FE and LP there are evidences that the distribution of adopters stochastically dominates the distribution of non-adopters. Using the distribution of productivity obtained with OP or the distribution obtained after controlling for sample and law adoption selection (Main) reverses the pattern present in OLS, FE and LP distribution, i.e, we do not have evidences that the distribution of adopters stochastically dominates the distribution of non-adopters.

Table VI.4 – Kolmogorov-Smirnov Tests

	H_0: Distribution are equal		H_0: Adopters Distribution Dominates	
Estimation Method	S_1	p value	S_2	p value
	(1)	(2)	(3)	(4)
OLS	0.222	0.07	-0.110	0.480
FE	0.307	0.004	-0.027	0.958
LP	0.108	0.828	-0.108	0.496
OP	0.237	0.046	-0.237	0.034
Main	0.272	0.014	-0.272	0.012

The mean comparison test, the graphical analysis and the Kolmogorov-Smirnov test point out the importance of controlling for sample selection, law selection and to allow productivity to be endogenous to the firm. We have that estimating the production function using OLS, FE, LP and OP generate productivity measures that imply that adopters are on average more productive (or equally productive) than non-adopters. In some cases, we also have evidences of stochastic dominance of the productivity distribution of adopters over non-adopters. On the other hand, when we consider the productivity measure estimated with our algorithm (Main), the results are the opposite.

The reversion in productivity mean and distribution found when we compare Main estimates with alternative estimates is associated with the fact that adopters have on average more capital than non-adopters (table VI.2 and figure VI.1). From our production function estimates (table VI.1) we have that OLS, FE and LP generate lower capital estimates. As a consequence, this bias leads to positive residuals and therefore higher inferred productivity for firms with larger capital stocks. Since we have a positive relationship between capital and adoption, we will also have that OLS, FE and LP will attribute a higher productivity to adopters.

VI.3 Determinants of Firm Survival

Table VI.5 displays the results of productivity and capital mean comparison tests between the group of firms that exit the sample at some point and firms that stay in the sample the whole period.

As it can be seen from table VI.5, firms that leave the market at some point are on average more productive and have a smaller capital stock. However, we cannot reject that the means of these variables for both groups are equal.

Table VI.5 – Capital and Productivity Mean Test - Firms that survive X Firms that Exit by 2009

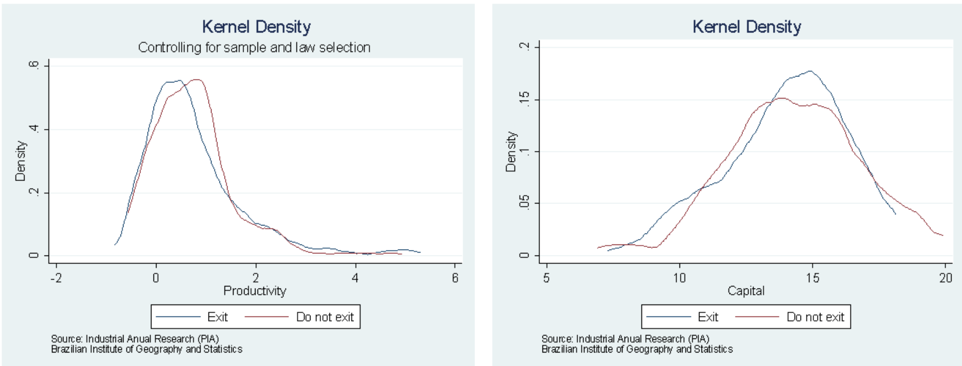
	Survive	Exit by 2009	Δ	t statistics
Capital	14.34	14.02	0.32	1.47
	(0.131)	(0.166)	(0.218)	
Productivity	0.726	0.743	-0.017	-0.215
	(0.041)	(0.071)	(0.077)	
# Obs.	371	190		

Standard Errors in Parentheses.

In addition to the mean comparison test, we also compare productivity and capital density estimates by firm status (figure VI.3). The fact that productivity and capital density functions of the firms that stay in the sample during the whole period are slightly shifted to the right when compared with the density functions of firms that exit at some point is consistent with the evidence that firms that stay the whole period are on average more productive and have a greater capital stock.

Figure VI.3 – Productivity and Capital Kernel Density Estimates - Exit by 2009 vs. Survivors

(VI.3(a)) Productivity (VI.3(b)) Capital



VI.4 Productivity Growth

To explore productivity growth we construct a measure of aggregate productivity given by the following equation:

$$\omega_t^C = \frac{1}{N_C} \sum_{i \in C} \hat{\omega}_{it}, \quad t = 2000, ..., 2009 \tag{1}$$

where $\hat{\omega}_{it}$ is firm productivity and C can be the full set of firms at year t, the set of adopters at year t or the set of non-adopters at year t. In order to calculate productivity growth rate we use the following equation: $\frac{\omega_t^C - \omega_{t-1}^C}{\omega_{t-1}^C}$.

Table VI.6 presents the rate of productivity growth considering all firms (column 1) and by firm status (columns 2 and 3). As we can see the productivity growth in the industry and by firm status is extremely volatile. In some years like 2003 and 2006 productivity grows at a high rate. On the other hand at periods like 2005 and 2009 productivity falls sharply. Moreover, the comparison of the average productivity growth suggests that adopters productivity evolves at a faster pace than non-adopters productivity during the time spam of our sample. At first sight this result seems to indicate that the Informatics Law has a positive effect on the industry. However, we should take it with a grain of salt. The problem is that our measure of productivity captures all the non observed factors that generate revenue to the firm. Since the Informatics Law gives to the firm a tax exemption, we cannot state if the higher rate of growth in adopters productivity is generated by the tax exemption or by the R& D investment.[4]

[4]It should be pointed out that this result is robust to the measure of aggregate productivity; constructing aggregate productivity using firm market-share as the weight given to each firm generates the same pattern of productivity growth in the industry and by firm status displayed at table (VI.6).

Table VI.6 – Productivity Growth Rate by Firm Status

	Productivity Growth(%)		
	(1)	(2)	(3)
	Industry	Non Adopters	Adopters
2001	-5.8	-7.1	15.3
2002	-16.3	-9.7	-8.1
2003	29.2	17.0	60.6
2004	10.0	8.0	-4.2
2005	-19.2	-19.2	-30.3
2006	39.2	29.2	117
2007	13.9	16.4	0.4
2008	-0.8	-7.8	23.9
2009	-22.8	-14.3	-57.2
Average	3.0	1.4	13.1

VII
Policy Implications

Ribeiro et al. (2010) follow the literature in policy evaluation [Imbens and Wooldridge (2008)] and assess the effectiveness of the Informatics Law in promoting productivity gains by comparing the difference in means between control and treatment group before and after law adoption (Differences-in-Differences - DID). More specifically, they apply a Fixed Effect estimator in a model where the estimated measure of productivity is the dependent variable and the independent variables are a dummy that is equal to one when the firm adopts the law and zero otherwise, year dummies and additional firm controls.

In the DID estimator the identification of the policy impact on productivity relies on the hypothesis that there is a exogenous source of variation affecting treatment assignment, trends in both treatment and control groups are the same before the intervention and that there is no spill over on the control group, i.e, on firms that do not adopt the law (there is no general equilibrium effect). The problem is that given characteristics of the Informatics Law - self-selection, tax exemption, imposition to invest in R&D and local content requirement in purchase of materials - none of the required hypotheses seem plausible. Therefore the DID estimator will not recover the correct effect of the Informatics Law over productivity.[1]

[1] For the sake of curiosity we have run the DID regressions with all estimated measures of productivity. When the measure used is the one obtained with OLS, FE or LP the coefficient associated with the impact of the Informatics Law is positive and significant only in the case of the FE productivity estimate. In the regressions where productivity measure is obtained with OP or with our algorithm the estimated effect of the Informatics Law is negative but not significant.

Since we cannot use policy evaluation methods, the analysis of the impact of the Informatics Law over productivity is dubious. First we found that adopters are selected from a pool of larger, less productive firms. We also have that adopters face a lower attrition rate [table (III.1)]. These two facts are an evidence that the Informatics Law contributes to maintain less efficient firms in the industry. On the other hand table (VI.6) suggests that adopters productivity grows at a higher rate than non-adopters. At first sight the higher rate of growth of adopters productivity suggests that the Informatics Law has been effective. The problem with this conclusion is that given our measure of productivity, it is not possible to identify if the higher rate of productivity growth of adopters is due to the tax exemption or due to the R&D investment.

VIII
Robustness Analysis

In this section we make a series of robustness checks in the results of the production function estimates. We test whether our production function estimates depends on the optimization algorithm used to minimize the moment conditions in the second step of our procedure. We also test if changing the sample used generates different patterns in production function estimates.

The estimates provided at table VI.1 are obtained using the non linear least squares to minimize the moment conditions given by equations (14) and (15). In order to confirm if the parameters obtained are the solutions of the optimization problem we perform an alternative optimization algorithm using a grid search method. Table VIII.1 column 1 displays the estimates with the grid search optimization algorithm. As we can see, the estimates of capital and materials coefficients are practically identical to the estimates provided at table VI.1 column 5, confirming that we succeeded in finding the optimal solution.

Table VIII.1 – Alternative estimates Production Function - Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)
	Grid Search	Modified Sample				
	Main	OLS	FE	LP	OP	Main
Labor	0.053	0.108	0.277	0.049	0.016	0.046
	(0.049)	(0.042)	(0.063)	(0.041)	(0.036)	(0.044)
Capital	0.26	0.155	0.061	0.09	0.252	0.261
	(0.092)	(0.028)	(0.032)	(0.044)	(0.088)	(0.167)
Materials	0.77	0.567	0.346	0.76	0.571	0.812
	(0.223)	(0.033)	(0.066)	(0.215)	(0.026)	(0.326)
N	561/271	600	600	600	501	600/290
Returns to Scale	1.083	0.830	0.684	0.899	0.839	1.119
P values*		0.000	0.002	0.628	0.082	0.693
Year dummies	yes	yes	yes	yes	yes	yes

Columns 2 through 6 display alternative production function estimates using a different sample. Instead of using a sample of firms with the mode of industrial classification equal to 30 (CNAE 30) we use a sample of firms that report their CNAE as being equal to 30 in each year. To make the difference between samples clear, consider the following example: suppose a firm that stays active in all periods but reports their CNAE as 30 in seven years and a different CNAE in the remaining three years. The sample considered in the main estimations of the paper would take the full account of this firm, i.e, all ten years would be included in the sample. On the other hand, the sample used in the robustness analysis would only consider the seven year time span in which the firm reported CNAE equal to 30.[1]

Table VIII.1 shows that changing the sample does not generate a different pattern in the production function estimates and in the estimated return to scale of the computer industry. Capital estimate obtained with our algorithm is higher than OLS, FE and LP but lower than OP. Like the estimates provided before, labor coefficient obtained with our approach is

[1]Here it is important to highlight that the exit variable would not change, i.e, in the sample used to perform the robustness check we do not consider the change in industrial classification as being equal to the firm leaving the market.

higher than OLS but lower than FE. Moreover, LP and OP labor estimates are not significant.

IX
Concluding Remarks

In this paper we develop a model of endogenous productivity change that takes into account the selection generated by firm exit over time and firm self-selection to receive the government benefits of the Informatics Law. While previous literature treated the possibility of endogenous productivity and the issue of firm selection into the sample separately, we build a model that takes both into account. Moreover, we departure from the previous literature by modeling two types of firm selection, i.e, our model considers the selection generated by exit of firms and the selection of firms in the Informatics Law.

Applying our approach to an unbalanced panel of 154 firms in the Brazilian computer industry we obtain production function estimates that are robust to the bias generated by firm attrition and by selection into the Informatics Law. With the correct estimates of the production function parameters we construct a measure of firm productivity and compare it with productivity measures obtained with alternative methods. We find that alternative productivity measures indicate that adopters are on average more (or equally) efficient than non-adopters. When we use our correct productivity measures we find the opposite.

The reversal in productivity distribution found when we consider our approach vis-à-vis alternative approaches is associated with lower capital estimates found by alternative methods and with the fact that adoption is positively related to capital. Due to the negative bias in capital estimates, alternative methods lead to positive residuals and, as a consequence, higher inferred productivity for firms with larger capital stocks. Since we have a positive relationship between adoption and capital, we conclude that alternative approaches will attribute a higher productivity to adopters.

Moreover, we have that adopters are on average larger, less efficient and face a lower attrition rate than non-adopters. On the other hand, the productivity of adopters grow at a higher rate than the productivity of non-adopters. However, since we do not have enough information to identify what is actually generating this increased rate of growth we cannot make any statement about the effectiveness of the Informatics Law.

A key message of this paper is that using a measure of productivity that is estimated ignoring the possibility of self-selection in the Informatics Law will bias our policy conclusions. This result points out to the importance of considering the specificities of the industry analyzed in the estimation of the measure of productivity instead of blindly relying on the traditional estimation procedures.

X
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XI
Appendix

Appendix A: Variables Construction

In this appendix, we describe how the variables were constructed. It is important to point out that all variables are in 2008 reais. Revenue and materials are deflated with the three digit industry deflator - *Índice de Preços ao Produtor Amplo* (IPA). Capital and investment are deflated using a gross capital formation index.

- Output: We use as our measure of output the net sales revenue. In PIA database, this variable is coded as x14.
- Labor: We use as our measure of labor the total number of workers in production. In PIA database, this variable is coded as x03.
- Capital: We construct the capital variable using the perpetual inventory method. The depreciation is obtained adding the following variables: x67, x68, x69 and x70. The investment is calculated adding the following variables: x55, x56, x57, x58, x59, x60, x61, x62, x63, x64, x65 and x66.
- Materials: As our materials measure, we use the value of intermediate consumption (raw materials and components). In PIA this variable is coded as x26.
- Market-Share: Our measure of market-share is given by the firm revenue share. To construct this variable, we first sum the revenue of all firms within the same two digit industry for a given year and find the total industry revenue. After that, we find the ratio firm revenue/total industry revenue. This ratio is our measure of market-share.
- Firm share in national materials market: The key variable to construct the firm share in the national materials market is the PIA variable

percnac which gives the percentage of national inputs used in the production by each firm. We first find the total amount of national materials used by each firm. To do that, we multiply the materials variable by the *percnac* variable. In the next step, for a given year we add the firm amount of materials within a three digit industry and find total amount of national materials. Finally, we find the ratio between firm amount of national materials and total amount of national materials within three digit industry. This ratio is our variable of firm share in national materials market.