Effects of Patent Infringements on Innovation and Labor Market Outcomes: Evidence from Brazil

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Abstract

We evaluate the effects of violating the intellectual property rights of patents, as established by the generic drug law, on innovation and labor market outcomes in Brazil. Our empirical results suggest that the patent infringement law stimulates innovation, as evidenced by an increase of 30.2-40.0% in patent applications. Our results show that the number of employees increases by 6.2% and the number of inventors increases by 6.4% across innovator firms. Our results also suggest an increase of 8.1% in real average hourly earnings. To reconcile these results, we demonstrate that a country with a high degree of resource misallocation potentiates the positive effects of patent infringement on innovation outcomes. Patent infringements also generate a labor reallocation effect on innovator firms post-intervention.

Keywords: Innovation and Invention, Intellectual Property, Industry Studies.

JEL code: O31, O34, L65.

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1 Introduction

Since the start of the COVID-19 pandemic, several policymakers have considered adopting patent infringement on new vaccines. However, there is a discussion on the social gains of violating the intellectual property rights (IPR) of patents because IPRs influence the innovation incentives and the availability of new goods (Helpman, 1993; Klette and Kortum, 2004; Acemoglu and Akcigit, 2012). In the case of developing countries, this issue is particularly relevant because of the distance from the technology frontier (Acemoglu and Linn, 2004; Dechezleprêtre et al., 2016; Qian, 2007) and resource misallocation (Hsieh and Klenow, 2009; Oberfield, 2013; Vasconcelos, 2017). Focusing on this issue, we have used the generic drug law established in Brazil as a patent infringement experiment. Thus, we evaluate how these exogenous changes in IPRs influence innovation and labor market outcomes.

Our results show that the Brazilian Generic drug law has caused a relative increase in patent innovations and a corresponding decrease in the number of inventors. Specifically, our empirical results suggest that the patent infringement law has influenced pharmaceutical innovation, as is evidenced by increases of 30.2-40.0% in patent applications, while the number of inventors decreased by 6.4%. Patent infringement has influenced labor market outcomes for innovator firms. Our results show an 8.1% increase in real average hourly earnings, while the number of employees in pharmaceutical innovator firms has decreased by 6.2%. The real average hourly earnings of inventors decreased by 2.4%. Our results also show labor reallocation within innovator firms based on gender and race factors. Overall, pharmaceutical innovator firms pay higher earnings to women and non-white employers after a patent infringement shock. The change in employees is higher for white and male employers after this shock.

To obtain the previous results, we merge three administrative sets from Brazil: patent data, employer-to-employee data, and entrepreneur register data. Using these databases, we build an unbalanced firm-quarter panel between 1996q1 and 2018q4. Using the Generic drug law established in 1999 as an exogenous shock and a technology-based group as a cross-section variation, we use difference-in-differences. In contrast to other studies such as Acemoglu and Linn (2004), we focus on the technology group instead of the economic sector to reduce any selection bias by a firm's crossovers, and because the patent office defines the International Patent Classification (IPC). We also demonstrate that the results for innovation outcomes are overestimated when this issue is ignored. Using this identification strategy, we focus on a staggered treatment adoption design because the patent infringement effects might be heterogeneous and the timing of the innovation varies across firms (SantAnna and Zhao, 2020).

To reconcile these empirical results, we develop an endogenous growth model with heterogeneous firms and input wedges. The model is inspired by the one used in Aghion et al. (2005), except for the use of output distortions, as in Hsieh and Klenow (2009). We demonstrate that an innovation-guided economy with a high degree of resource misallocation potentiates the effects of patent infringement on innovation and on labor market outcomes. Corroborating our empirical results, the main theoretical predictions suggest that patent infringements cause an increase in innovation rates, a decrease in labor costs with Research & Development (R&D), and an increase in the innovation wage premium. Moreover, in the presence of heterogeneous workers, patent infringement causes skill-based labor reallocation.

Within the literature on firm dynamics, the main results are applied to the theoretical findings. Our study is related to other studies that suggest that IPR influences innovation and firm dynamics because it ensures post-innovation profit while enhancing pre-innovation costs (Klette and Kortum, 2004; Aghion et al., 2005, 2009; Acemoglu and Akcigit, 2012; Akcigit and Kerr, 2012; Aghion et al., 2015). Our study converges to the prevalence of the positive effects of patent infringement on innovation outcomes, such that the rent dissipation effect is higher than the effect of escaping from competition. This study is close to that of Acemoglu and Linn (2004) ,Qian (2007) , Dechezleprêtre et al. (2016) as it also provides evidence that skill-based labor reallocation in innovator environments complement patent infringements of pharmaceutical goods (Jaravel et al., 2018; Akcigit et al., 2017; Bernstein et al., 2018).

The remainder of this study is organized as follows: in Section 2, we present the background of the Brazilian Generic Drug Law, the data, and the econometric issues involved; in Section 3, we present the empirical evaluation; in Section 4, we present a theoretical model to reconcile our empirical results; Section 5 concludes this study.

2 Empirical check

Here, we evaluate the effects of patent infringement on innovation and labor market outcomes in Brazil as a result of the Generic drug law established in 1999.

2.1 Background on the Brazilian Generic Drug Law

The Brazilian Generic Drug Law was promulgated on February 10, 1999. This law allows for infringement of pharmaceutical patent innovations in Brazil. The goals of the law are to promote competitiveness in the Brazilian pharmaceutical market, and to increase the population's access to pharmaceutical goods. In other words, the law seeks to increase access to high-quality, low-cost drugs. According to the Brazilian Health Regulatory Agency (ANVISA), patent infringement requests increased by 1836.14 % between 2000 and 2006.

The Brazilian government also implemented concomitant factors with the generic drug law. First, a new regulatory protocol ensured the pharmaceutical equivalence of generic drugs to branded drugs. Second were the educational campaigns regarding generic drugs. Third, production incentives given to new firms included the provision of subsidized public credit. Fourth, the priority is to purchase generic drugs for public health. The first two guaranteed confidence of the population in the new drugs, while the last two guaranteed the initial condition of the pharmaceutical market for new firms.

2.2 Administrative Data sets

We use three administrative data sets: patent, employer-to-employee, and entrepreneur register, choosing the period between January 1996 and December 2015 to attenuate some selection biases due to the backlog of patent applications. Thus, we use an unbalanced firm-quarter panel of 65850 innovator firms across 79 quarters (1,203,342 observations). The datasets used are described below.

Patent data. *Banco de Dados de Propriedade Intelectual* (BADEPI) is a patent database from the Brazilian National Institute of Industrial Property (INPI). This database contains all patent applications filed in Brazil since 1996. Patent applications can be accepted or rejected. We have two information levels: innovators, who are the owners of innovative goods, and inventors, who are the creators of innovative goods. The identities of both agents has become unique over time. This database provides information about the day of application, day of patent registration, localization, and technical fields (International Patent Classification, IPC). Each patent application can have more than one innovator, as well as more than one inventor. Each patent application can be present in more than one technical field.

Employer-to-employee data. *Relação Anual de Informações Sociais* (RAIS) is a matched employer-employee dataset assembled by the Brazilian Ministry of Economy and provides a high quality census of the Brazilian formal labor market. We utilized RAIS data spanning the period from 1996 to 2018. The data consists of job records identified by the combination of a worker ID number and a plant registration number. These identifiers are unique and do not change over time, thus allowing us to track workers over time and across establishments. Plant-level information includes the geographic location, industry sector, and legal status. Employee-level information includes gender, age, education, earnings, tenure, and occupation. By matching BADEPI with RAIS, we are able to map the labor market outcomes of innovator plants.

Entrepreneur register data. We used the public database of Brazilian plants provided by the Brazilian Internal Revenue Services. This database provides the following information for each plant: their legal code; start date of their activities; end date of their activities; the reason for exit and the current situation; and basic details such as location, size, and sector. It also provides information about the 44 million legal entities registered in Brazil including the following details: entrepreneur identity, entry date, position occupied in entrepreneurship, and identity of the legal representative for each entrepreneur. Matching BADEPI, RAIS, and the Entrepreneur register data, we map the dynamics of innovator and non-innovator plants. We define an innovator firm as one with at least one patent application or in which at least one of the owners is a patent applicant.

2.3 Econometric issues

We denote the outcome of interest as Y_{imt}, which includes innovators' outcomes, patent applications, technical-augmenting patent applications, and the number of innovators; labor market outcomes, such as real average hourly earnings, number of employers, and real average hourly earnings of inventors. To provide evidence in favor of the parallel trends assumption, and to attenuate the potential biases that can result from applying a standard DID, we estimate the following equations:

$$\begin{aligned} Y_{imt} &= \sum_{\tau=-2}^{-q} \beta_\tau \left(\text{Pharmaceutical Technology}_m \times \text{Generic Drug law}_\tau\right) \\ &+ \sum_{\tau=0}^{m} \beta_\tau \left(\text{Pharmaceutical Technology}_m \times \text{Generic Drug law}_\tau\right) \\ &+ \mu_i + \lambda_t + X'_{it}\Gamma + \epsilon_{it} \end{aligned} \tag{1}$$

where μ and λ are state (4-digit sector x city) and time (quarters) fixed effects, respectively, X are covariates (wage bill, tenure, and square of tenure), and ϵ is an unobserved error term. The above equation includes anticipatory effects, q, and post-treatment effects, m.

Our coefficient of interest, β, represents the average within-firm change in our outcome variables for firms in the pharmaceutical technological group. The pharmaceutical technological group is a treated group and represents firms with at least one patent application for pharmaceutical technology, more specifically, one patent with a technical field classified as the Medical or Veterinary Science and Hygiene (IPC A61). The non-pharmaceutical technological group is a control group and represents firms with patent applications unrelated to pharmaceutical technology in any period.

We rely on a DID strategy with a staggered treatment adoption design to exploit the fact that firms innovate in different periods. Thus, we use SantAnna and Zhao (2020)'s estimator to estimate the dynamic treatment effects. Another advantage of this estimator is the attenuation of any possible biased effects due to the staggered timing of entry of new innovators.

2.4 Measurements and robustness issues

Seeking to better identify the patent infringement shocks, we focus on a quarter as the time definition. We do this instead of the month because of the multiplicative seasonal effect of labor market outcomes. In the Appendix, we replicate the main results at the monthly level. Overall, the main results do not change magnitude or trend. We restricted ourselves to analyzing the firm and not the plant because of the higher number of patent applications for businessmen and scientists in Brazil. There were very few regional patent offices in the 90s. During this period, it was less bureaucratic for the owner of the plant to patent the property in his/her name.

We restrict the sample to private firms because Brazil has an overpaid public sector (Cavalcanti and Santos, 2021), which might influence the labor-market variables. We also use all firms that have at least ten employees, expecting firms in sectors such as (i) education; (ii) domestic services; and (iii) extra-territorial organizations. As a robustness check, we further restrict the sample excluding firms in sectors such as (iv) agriculture, hunting, and forestry; (v) fishing; (vi) hotels and restaurants; (vii) finance and securities services; (viii) real estate, renting, and business activities; (ix) administrative services; (x) public administration and defense; (xi) compulsory social security; (xii) arts, culture, and sports. The exclusion of firms from these sectors reduces the control group. Overall, the main results are attenuated when we exclude the sectors mentioned above.

We also examined if the definition of the treatment group guided the main results. This is because patent infringement can influence the incentives of new innovators. This increases the number of new innovators in the pharmaceutical industry, whereas this may not change the number of new inventors in the non-pharmaceutical group. However, in the sample, the number of innovators does not change substantially across groups over the quarters, primarily in the non-pharmaceutical group. Another relevant point is that the patent office defines the IPC. We believe that this reduces the problem. As an additional check, we also use the register data to define the treatment group as the pharmaceutical sector (2-digital of the Brazilian classification of economic activity = 21), similar to the definition used by Acemoglu and Linn (2004). In this check, the control group is another sector excluding arts, culture, sports, administrative services, finance and securities services, real estate services, and domestic services. In our sample, 6726 firms are in the innovator pharmaceutical group but not in the pharmaceutical sector and 63 firms are in the pharmaceutical sector but not in the innovator pharmaceutical group. Between 1997m8 and 2002m11, which is the focal periods of the main results, the total of these crossovers were 928 and 22, respectively. Overall, the results of this check are qualitatively identical when we change the definition of the treatment groups.

Focusing on the parallel trend assumption before the Brazilian generic drug law (1996m1-1999m1 period), Table 1 shows the conditional difference of interest outcomes between and within-group firms. Although there is a significant difference in labor market outcomes between innovator and non-innovator firms, there is no significant difference between innovator firms. In terms of innovation outcomes, there is no significant difference between the innovation outcomes and labor market outcomes. We also check for these differences between firms in the pharmaceutical sector and those in the non-pharmaceutical sector. We do not observe a parallel trend in this robustness group and present this check in the Appendix.

Excluding differences in sector-city economic conditions as the driving force behind our results, we confirm the robustness of our empirical findings to flexibly control for sector-city quarter-specific trends. We also control for differences in the wage bills and tenure across firms, suggesting that our results are not driven by disproportionate changes in the labor requirements of pharmaceutical innovator firms. We measure covariates in 8-quarters before the generic drug law and interact them with the post dummy instead of including time-varying covariates, to avoid the issue of bad controls. This issue may be present in our setting as patent innovation is known to affect other firm outcomes. We show the estimates with predetermined covariates in the Appendix. These robustness results are qualitatively identical to the main results.

While we show estimates using logarithmic values of the dependent variables, we also show estimates in terms of growth rates of the dependent variables. Overall, the results are similar to the main results. However, the results of the patent applications are difficult to interpret and compare. In the Appendix, we estimate the main results using dependent variables in the form of growth rates. Another relevant issue is that the labor market outcomes might be seasonal; therefore, we use these variables as a 12-month average. The technological nature of the patents within and between groups might imply a sensitive measurement of innovation in the DID estimations. As these measurements capture the flow of innovation, we measure the patent stock and technical-augmenting patent stock as measures of the innovation. Using NBER US patent citations and OECD patent citations, we also try to quantify citation-weighted patents in Brazil. Unfortunately, matching our data with PCT, only three patents from Brazilian firms have citations in the US and EU offices. This might be an issue of measurement or a consequence of the fact that Brazilian patent applications generate a lower knowledge diffusion across posterior patent applications while Foreign patent applications generate a higher knowledge diffusion, as suggested by Vasconcelos and Van Doornik (2022).

Finally, we add the firm fixed effects and quarterly sector-city fixed effects to all estimations. The sector is a 4-digit representation of the Brazilian classification of economic activity, and the local is the city of the main plant. All the standard errors are clustered at the firm-quarter level. All nominal values are deflated using the Brazilian National Consumer Price Index (IPCA). We work with an unbalanced firm-quarter panel; thus, we interpret the next result as the quarterly average difference between the pharmaceutical innovator firms (treated) and the non-pharmaceutical innovator firms (control).

3 Empirical Results

Here, we show the results from evaluating the effects of patent infringement on innovation and labor market outcomes in Brazil. Table 1 and Figure 1 show the main results. Figures 2–5 show additional results. The results are described in the following sections.

3.1 Main results

Table 2 shows the DID coefficient based on equation 1 (i.e. average treatment effect on treated), while figures 1 show the dynamic DID plots. Each row and column of table 2 exposes a result with each row representing a dependent variable and each column representing a specification. Column (1) exposes estimations without the covariates and medium-run period (1996m2-2015m12); column (2) exposes estimations with the covariates and medium-run period; column (3) exposes estimations without the covariates and short-run period (1997m11-2005m11); Column (4) exposes estimations with the covariates and short-run period. We focus on the estimated results with covariates. Column 4 of Table 2 represents the DID coefficients of the results in Figure 1.

Innovation outcomes. Considering a measure of stocks, patents are 13.9% higher in pharmaceutical innovator firms than in non-pharmaceutical innovator firms in the medium-run period post the Generic drug law. In the short-run period, which is less subject to confounding effects, the estimated effect is 6.2%. Moreover, the technical-augmenting patents are 15.3% higher in pharmaceutical innovator firms than in non-pharmaceutical innovator firms in the medium term. In the short term, the estimated effect of technical-augmenting patents is 8.0%. The number of inventors is 11.1% lower in pharmaceutical innovator firms than in non-pharmaceutical innovator firms in the medium term. In the short term, the estimated effect on the number of inventors is -6.4%. However, these results are consistent and survive the exclusion of covariates and changes in the period covered.

The dynamic effects of infringement on patents and technical-augmenting patents are positive and have increased over time. Twelve quarters after the promulgation of the Brazilian Generic drug law, patent applications are 37.8-41.8% higher in pharmaceutical innovator firms than in non-pharmaceutical innovator firms. The dynamic effects of patent infringement on the number of inventors are negative and have increased over time. Twelve quarters after the promulgation of these laws, the number of inventors is 8.0% lower in pharmaceutical innovator firms than in non-pharmaceutical innovator firms. Thus, there is evidence that the Brazilian Generic drug law has caused a relative increase in patent innovations and a decrease in the number of inventors.

Labor Market outcomes. Table 2 also shows that the number of employers is

4.1% lower in the short-run period in the Pharmaceutical group, while it is 8.1% lower in the medium-run period. Wages are 8.1% higher in the medium run, while we do not obtain a significant result in the short-run period. These results suggest that the wage premium growth in Pharmaceutical innovators might not be sufficient to inhibit labor reallocation within the innovator firms. Moreover, the innovator wages are 2.4-2.9% lower in the pharmaceutical innovator firms than in the non-pharmaceutical innovator firms. The lower innovator wages might be a consequence of the increased demand for inventors in the pharmaceutical innovator group post the allowing of patent infringement. Comparing these results to the effects on workers, the effect on the number of inventors is less negative than the effect on the number of employees, but the effect on the wages of an average employee is positive while the effect on the wages of inventors is negative. This can be evidence for the skill-based reallocation of employees, and mainly, reallocation of talent.

Twelve quarters after the promulgation of the Brazilian generic drug law, the number of employees is 2.9% lower in pharmaceutical innovator firms than in non-pharmaceutical innovator firms. The dynamic effects of patent infringement on the average wage are 6.4% higher in pharmaceutical innovator firms than in their non-pharmaceutical counterparts. The dynamic effects of patent infringements on inventors' wages are 2.3% lower in pharmaceutical innovator firms than in non-pharmaceutical innovator firms. Fewer inventors with lower wages represent lower labor costs of inventors for firms. Thus, there is evidence that the Brazilian generic drug law has caused a relative reduction in the labor costs of R&D.

3.2 Robustness checks and Additional results

Restricted sample. Figure 2 shows the main results (for all firms) and dynamic DID estimates when we exclude non-profit-maximizing firms from the sample (Private firms). Overall, the positive effects of patent infringements are lower when we include the Private firms. Twelve quarters after the promulgation of the Brazilian Generic drug law, patent applications are 27.8-31.8% higher in the pharmaceutical innovator firms than the non-pharmaceutical innovator firms. The coefficient estimates of the labor market outcomes do not change quantitatively. In Brazil, non-profit-maximizing firms are mostly large public firms. Moreover, in the public sector, employees have more stable jobs and wage stickiness. Thus, these facts and our results suggest that if there is a skill-biased reallocation effect, this is mitigated by the profit-maximizing behavior of the firms.

Economic sector. Using the pharmaceutical sector as the treatment group and the non-pharmaceutical sector as the control group, we estimate the previous exercises. Figure 3 shows that there are no statistical significance differences from the main results. Despite the patent infringement shock influencing the innovator groups, and not necessarily the sectors, pharmaceutical innovators are mostly in the pharmaceutical sector. The exceptions are public universities; however, we exclude them from our estimates.

Education and Occupation. [in next draft]

Gender and Race. [in next draft]

4 Schumpeter-theoretical mechanisms

To formalize the innovation effects of patent infringement, we develop an endogenous growth model with heterogeneous firms and output distortions. The model is inspired by the one used in Aghion et al. (2005), except for the use of output distortions, as in Hsieh and Klenow (2009).

4.1 Environment

Consider an economy with an infinite horizon and continuous timing.

Households. There is a continuum of i-individuals with standard preferences regarding the consumption of a final good produced domestically, C; the utility function is given by

$$E_0 \int_0^\infty \ln C_i(t) e^{-\rho t} dt, \tag{2}$$

where $\rho \in (0, \infty)$ is the rate of time preference. The budget constraint of individuals is:

$$P_t C_{it} + Q_{it} B_{it} \leq \int_0^1 W_{it}(j) N_{it}(j) dj + B_{it-1}, \tag{3}$$

where P is the aggregate price, B is a risk-free asset, W is the wage of the labor hours in production.

Producers. The final good Y_t is produced using the intermediate inputs of X_{st}. Each j-firm in sector s produces intermediate goods. The production function of the final good is given by

$$Y_t = \int_0^1 \int_0^1 \log X_t(s,j) dj ds. \tag{4}$$

Firms are heterogeneous between sectors, while firms are homogeneous within sector because this we omit j index. Using technology A_{st} and the number of labor hours N_{st}, the production function of each firm is represented by

$$X_{st} = A_{st} N_{st}. \tag{5}$$

We assume that there is no mobility of capital or international labor. Assuming that labor is time-invariant and constrained in each economy.

Resource Misallocation. Similar to Hsieh and Klenow (2009), we define the distortions that increase the marginal products of labor as output distortions, $\tau_s \in (0,1)$. Output distortions influence the labor costs of employees. This distortion increases resource misallocation, and varies across sectors. We implicitly assume resource misallocation within sectors, disregarding any misallocation between sectors. This assumption renders the model tractable and able to be generalized. According to Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), the within-sector effect is the main source of resource misallocation.

Market structure. Let $\phi \in (0,1)$ denote the steady-state probability of markets being unleveled, where the nature of firms affects the future market structure. A firm's nature is characterized by its level of technology, output distortions, and labor costs. Moreover, firms can collude without costs or punishment. If firms engage in collusion, each firm can obtain a fraction $c \in (0, 0.5]$ of the leader's profits, thus leveling the market. Therefore, the higher the c, the lower the level of product market competition. In leveled group of sectors, we redefine $s = 0$ for all firms; in unleveled group of sectors, we redefine $s = 1$ for incumbent firms and $s = 2$ for following firms. Thus, we set $c = \pi_{0t}/\pi_{1t}$ as a measure of the competitiveness among firms, as in Aghion et al. (2005).

Innovation. We define z_{st} as the innovation rate of a firm such that $z_{st} = F(m_{st})$, where m_{st} is the number of innovators in each firm. Innovators are not internationally mobile. To increase its level of technology, each firm incurs a R&D costs, given by $(1+\tau_s)W_tG(z_{st})$. This moves the firm one technological step ahead of the Poisson hazard z_{st}. We suppose that $F(\cdot)$ is an increasing and strictly concave function subject to the Inada conditions and $G(z_{st}) \equiv F^{-1}(z_{st}) = (z_{st})^2/2$, such that $G(z_{st}) = (z_{st})^2/2$.

4.2 Static equilibrium

Equilibrium. Household problems are usually due to the log-preference assumption and the absence of a capital market. Thus, we focus on the firms' problems. Given the initial setting and equation 4, the demand functions for the intermediate goods are as follows:

$$X_t = \frac{Y_t}{P_t}. \tag{6}$$

The aggregate price is numerary of the economy. The equilibrium prices of the intermediate goods are

$$P_{st} = \begin{cases} \dfrac{(1+\bar{\tau})\bar{W}_t}{\bar{A}_t}, & \text{if sector is unleveled} \\ \dfrac{(1+\tau_0)W_{0t}}{A_{0t}}, & \text{otherwise} \end{cases} \tag{7}$$

where

$$\frac{(1+\bar{\tau})\bar{W}_t}{\bar{A}_t} = \sup\left\{\frac{(1+\tau_1)W_{1t}}{A_{1t}}, \frac{(1+\tau_2)W_{2t}}{A_{2t}}\right\}.$$

The above equilibrium equations indicate that there can be an unleveled sector without a large technological gap between firms. The higher the degree of efficient allocation or labor cost differences between firms, the lower is the dependence on the technological level to establish market leadership. Moreover, firm markups are endogenous and time-variant in unleveled markets, whereas they are exogenous and time-invariant in the leveled sectors. Thus, we define the static equilibrium as follows:

Definition 1. *In each period, the static partial equilibrium defines a sequence of optimal decisions for each firm j $\{X_{0t}, X_{1t}, X_{2t}\}_{t=0}^{\infty}$, a sequence of optimal wages $\{\bar{W}_t, W_{0t}\}_{t=0}^{\infty}$ for a given sequence of optimal prices $\{P_{st}\}_{t=0}^{\infty}$, and an initial distribution $\{\phi_s\}$ of firms in each period t.*

4.3 Dynamic equilibrium

Equilibrium. Now, we characterize the dynamic equilibrium.

Definition 2. *For the economy and firm j, the Markov perfect equilibrium is given by the optimal sequence $\{z_{st}, X_{st}, W_{st}, Y_t\}_{t=0}^{\infty}$ such that a sequence of prices $\{P_{st}\}_{t=0}^{\infty}$ and production levels $\{X_{st}\}_{t=0}^{\infty}$ imply that $\{z_{st}, P_{st}\}_{t=0}^{\infty}$ satisfies the equations 6 and 7; $\{z_{st}\}_{t=0}^{\infty}$ maximizes the expected value of each firm given the aggregate output $\{Y_t\}_{t=0}^{\infty}$, wages $\{W_{st}\}_{t=0}^{\infty}$ and the choice of R&D costs given the innovation rate $\{z_{st}\}_{t=0}^{\infty}$; the aggregate output $\{Y_t\}_{t=0}^{\infty}$ is given by the equation 4; and the labor market is in equilibrium for every time period given the sequence of wages $\{W_{st}\}_{t=0}^{\infty}$.*

We now define V_{st} as the expected value of each firm and $r_t \in (0, \infty)$ as the outside option for risk-free earnings. Each firm in the economy's innovation choice can be summarized by the following Bellman function:

$$r_t V_{1t} = \pi_{1t} - (1+\tau_1)\, W_{1t}(z_{1t})^2/2 - (z_{2t} + h)\,(V_{1t} - V_{0t}). \tag{8a}$$

$$r_t V_{2t} = \pi_{2t} - (1+\tau_2)\, W_{2t}(z_{2t})^2/2 + (z_{2t} + h)\,(V_{0t} - V_{2t}). \tag{8b}$$

$$r_t V_{0t} = \pi_{0t} - (1+\tau_0)\, W_{0t}(z_{0t})^2/2 + \bar{z}_{0t}(V_{1t} - V_{0t}) - z_{0t}(V_{0t} - V_{2t}), \tag{8c}$$

We define h as the duration of the patent; thus, patent infringement is defined as the reduction of patent duration. Given that we assume a one-step case innovation , we can recursively obtain Proposition 1. Further details of Proposition 1 are available in the Appendix. In the next subsection, we return to the implications for firm dynamics.

Proposition 1. *The equilibrium innovation rate for firms in unleveled markets is*

$$
\begin{aligned}
z_{1t} &= 0 && \text{(9a)} \\
z_{2t} &= -h - r - z_{0t} \\
&\quad + \sqrt{(-h - r - z_{0t})^2 + \frac{2c\pi_{1t} + (1+\tau_0)W_{0t}(z_{0t})^2}{(1+\tau_2)W_{2t}}} && \text{(9b)}
\end{aligned}
$$

while the equilibrium innovation rate for firms in leveled markets is

$$
\begin{aligned}
z_{0t} &= -h - r - z_{2t}\left(1 - \frac{(1+\tau_2)W_{2t}}{(1+\tau_0)W_{0t}}\right) && \text{(9c)} \\
&\quad + \sqrt{\left(-h - r - z_{2t}\left(1 - \frac{(1+\tau_2)W_{2t}}{(1+\tau_0)W_{0t}}\right)\right)^2 + \frac{2(1-c)\pi_{1t}}{(1+\tau_0)W_{0t}}},
\end{aligned}
$$

Unbalanced growth path.

Definition 3. *The unbalanced growth path (UGP) is a dynamic competitive equilibrium, characterized by uneven growth across the key aggregate variables.*

The aggregate innovation rate of each economy is given by

$$I_t = \phi(z_{2t} + h) + (1-\phi)z_{0t}.$$

In a steady state, the expected value of spending on innovation must be equivalent to the share of firms in the leveled and unleveled markets. Thus, we rewrite the aggregate innovation rate in each economy as

$$I_t = \frac{4z_{0t}\left(z_{2t} + h\right)}{2z_{0t} + z_{2t} + h}. \quad (10)$$

From equations 6, 9a, 9b, 9c, and 10, the aggregate innovation rate is a profit function.

The rate of innovation depends on the product market competition, output distortions, and labor costs in each sector. Finally, the Markovian perfect equilibrium guarantees a unique UGP equilibrium in which different intermediate goods firms grow at distinct and constant rates. Therefore, given the optimal allocation established by equations 4, 7, 9a, 9c, and 10, we can trace each sector equilibrium path.

4.4 Theoretical predictions and Empirical results

Following Aghion et al. (2005), this framework makes the following predictions: (i) the relationship between competition and innovation follows an inverted-U pattern, and the average technological gap within a sector increases with competition; (ii) more intense competition enhances innovation in frontier firms but may discourage it in non-frontier firms; and (iii) there is a substitutive relationship between patent infringement and product market competition in the context of fostering innovation. Adding output distortions, as in Vasconcelos (2021), we also obtain the additional prediction that (iv) the increase in the output distortions of firms in the leveled (unleveled) market causes a decrease (increase) in the innovation rate. Thirty theoretical predictions relate to the goal of the Brazilian generic drug law and our current focus.

See proposition 2. Further details of Proposition 2 are available in the Appendix.

Proposition 2. *Patent infringement causes an increase in the rates of innovation.*

Given that innovation rates are monotonic functions of patent applications, panels A and B of Figure 1 provide evidence for Proposition 2.

Proposition 2 implies corollary 1.

Corollary 1. *Patent infringements do not cause a decrease in the R&D labor costs.*

R&D labor costs are the wage bills of inventors and other labor costs including taxes. For a given unobservable labor cost, panels C and F of Figure 1 show a negative effect on the number of inventors and their wages. Consequently, this provides evidence for corollary 2.

For simplicity, we do not introduce uneven wages between the inventors and blue-collar workers — we do so in the Appendix. Inventors are regarded as a special type of worker with hard skills and creative minds. Adding this feature to the previous framework, Proposition 2 also implies Corollary 2.

Corollary 2. *Patent infringement causes an increase in the real average wages and in the innovation wage premium.*

Panels C-F of Figure 1 provide evidence for propositions 1 and 2. Unlike Aghion et al. (2005), exogenous patent infringement generates a positive innovation rate in the presence of micro-distortions. As in other developing economies (Hsieh and Klenow, 2009, 2012; Oberfield, 2013), Brazil's production experiences a high and persistent level of resource misallocation (Vasconcelos, 2017; Cavalcanti and Vasconcelos, 2021).

We focus on patents related to medical or veterinary science and hygiene, but we observe Total Factor Productivity (TFP) in the major sector of this technological field. Figure 8 shows the nominal TFP and real TFP across multiple years in the Brazilian manufacturing sectors for pharmaceuticals, medicinal chemicals, and botanical products. This figure shows that (i) the real TFP strongly decreases over the years, (ii) the nominal TFP strongly increases over the years, and (iii) there is a negative relationship between the real and nominal TFP. However, according to Hsieh and Klenow (2009); Restuccia and Rogerson (2013), the relationship between the two TPFs are given by

$$\underbrace{\log\left(TFPQ_{st}\right)}_{\text{Nominal TFP}} = \underbrace{\log\left(P_{st}\right)}_{\text{Sectoral price}} + \underbrace{\log\left(TFPR_{st}\right)}_{\text{Real TFP}}. \tag{11}$$

A guided theoretical explanation is that a substantial growth in the sectoral prices generates an increase in the nominal TFP, despite a decrease in the real TFP. As argued by Haltiwanger et al. (2018), this result can be related to an increase in the sectoral markup without any growth in productivity. This movement accelerate after the generic drug law in Brazil. Why? We demonstrate this in the next draft.

5 Final remarks

[in next draft]

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Table 1: Comparing firms between and within groups over predetermined period

Dependent Variables	Innovators × Non-Innovators	Pharmaceutical Innovators × Non-Pharmaceutical Innovators
	(1)	(2)
Wage (log)	0.386***	0.150*
	(0.017)	(0.089)
Wage of employers in high-skilled occupations (log)	0.368***	0,066
	(0.031)	(0.104)
Wage of high-educated employers (log)	0.459***	0.132
	(0.029)	(0.099)
Number of employers (log)	1.727***	0.413
	(0.066)	(0.321)
Share of employers in high-skilled occupations	-0.061***	0,011
	(0.008)	(0.014)
Share of high-educated employers	-0.058***	0.009
	(0.008)	(0.023)
Patent applications (log)		0,202
		(0.291)
Technical-augmenting patent applications (log)		0.132
		(0.299)
Innovator Wage (log)		0.249
		(0.190)
Number of Inventors (log)		0,013
		(0.081)
Firm FE	✓	✓
Sector#City#Time FE	✓	✓
Seasonal adjustment	✓	✓
Period covered 1996m1-1999m1	✓	✓
Clustered at the firm-month level	✓	✓

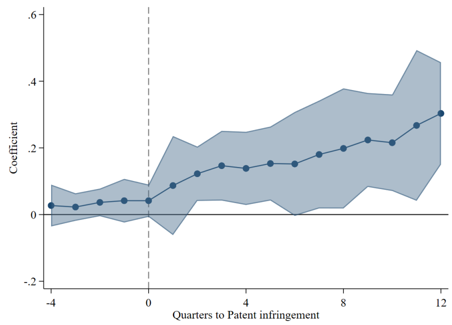
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Focusing 1996m1-1999m1 period, column (1) report the estimated difference between innovators firms and non-innovators firms. Column (2) report the estimated difference between Pharmaceutical innovator firms (Treated group) and Non-Pharmaceutical innovators firms (Control group). Estimates of the linear estimation including a dummy for predetermined innovator group. Clustered at the firm-month level, standard errors are reported in parenthesis.

Table 2: Effect of Patent infringement

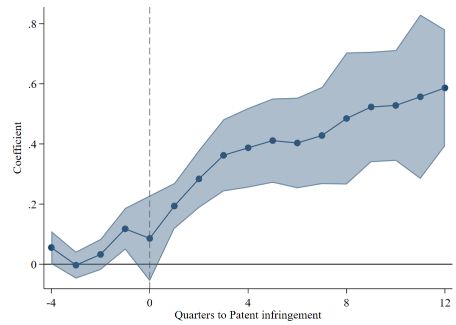
Dependent Variables	Pharmaceutical Innovators × Non-Pharmaceutical Innovators (1)	(2)	(3)	(4)
Patents (log)	0.157***	0.139***	0.066**	0.062**
	(0.046)	(0.045)	(0.029)	(0.028)
Technical-augmenting patents (log)	0.172***	0.153***	0.084**	0.080**
	(0.051)	(0.050)	(0.035)	(0.034)
Number of Inventors (log)	-0.246***	-0.111***	-0.117***	-0.064***
	(0.027)	(0.011)	(0.019)	(0.009)
Number of Employers (log)	-0.084***	-0.110***	-0.036***	-0.041***
	(0.012)	(0.011)	(0.010)	(0.009)
Wage (log)	0.121***	0.081*	0.059**	0.043
	(0.040)	(0.042)	(0.027)	(0.028)
Innovator Wage (log)	-0.071***	-0.029***	-0.042***	-0.024***
	(0.007)	(0.004)	(0.006)	(0.003)
Firm FE	✓	✓	✓	✓
Sector#City#Month FE	✓	✓	✓	✓
Clustered at the firm-quarter level	✓	✓	✓	✓
Seasonal adjustment	✓	✓	✓	✓
Covariates		✓		✓
Period covered 199602-2015m11	✓	✓		
Period covered 199802-2003m02			✓	✓

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Each row-column report one estimate of the average treatment effect on treated as the linear regression model specified in equation 1. Pharmaceutical innovator firms are the treated group such that each firm provides a patent innovation with at least one pharmaceutical technology (IPC A61 - Medical or veterinary science or hygiene); and Non-Pharmaceutical innovators firms are control group such that each firm never provides a patent innovation for this classification. Column 1 shows estimates without predetermined covariates, vis-a-vis, column 2. Predetermined covariates include the number of employers (in the log), average work experience (in years), square of average work experience, and share of employers in skilled occupations. All estimations absorb the state-time fixed effects (a dummy for each 4-digit sector, city, and month) and the firm fixed effects (a dummy for each firm). Standard errors, clustered at the sector-city level, are reported in parentheses. The number of observations are different across estimations (further details in the appendix).

Figure 1: Dynamic Effects of Patent infringement on Innovation and Labor market outcomes

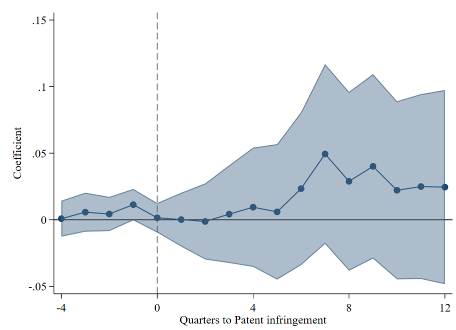


(a) Patents

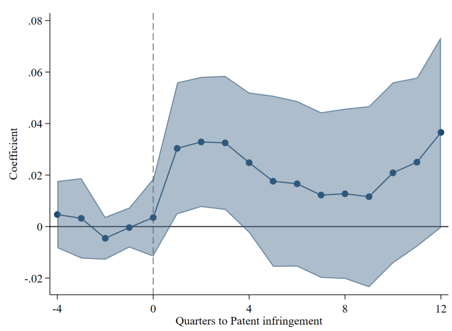


(b) Technical-augmenting Patents

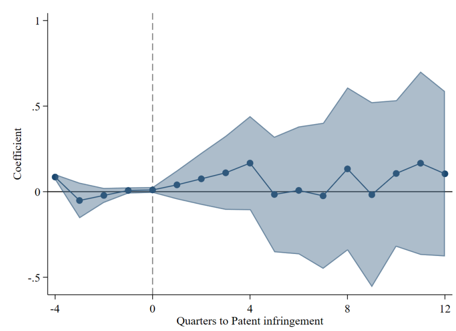
(c) Number of Inventors



(d) Number of employers



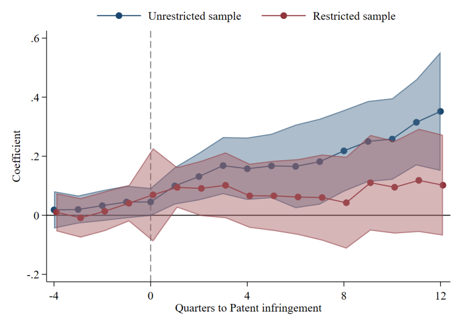
(e) Wage



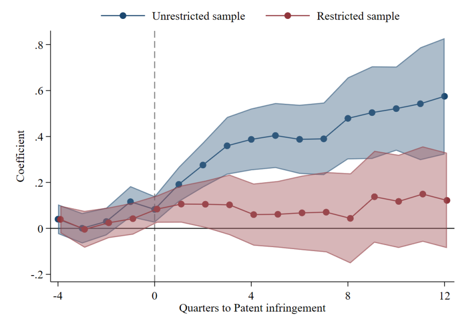
(f) Inventor Wage

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), Technical-augmenting Patent applications (panel B), on the number of inventors (panel C), the number of employers, average wage (panel E), and on the Innovator wage (panel F). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

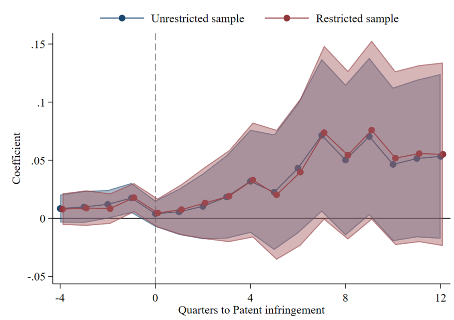
Figure 2: Dynamic Effects of Patent infringement on Innovation and Labor market outcomes



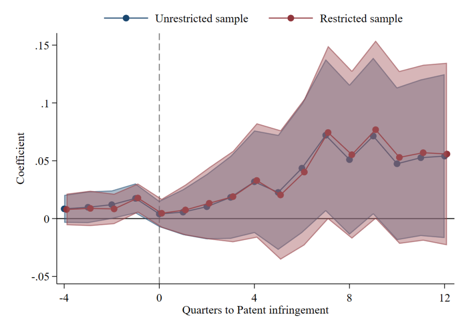
(a) Patents



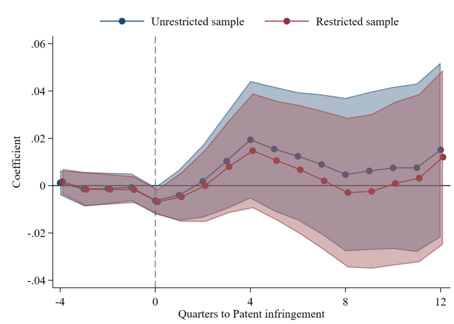
(b) Technical-augmenting Patents



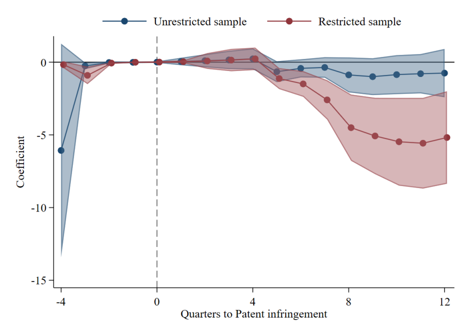
(c) Number of Inventors



(d) Number of employers



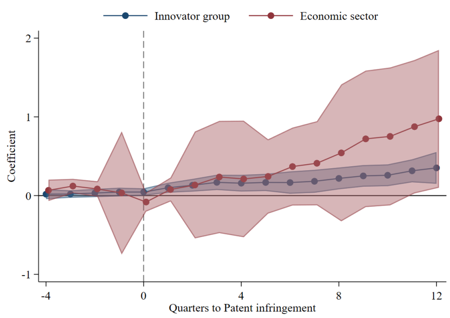
(e) Wage



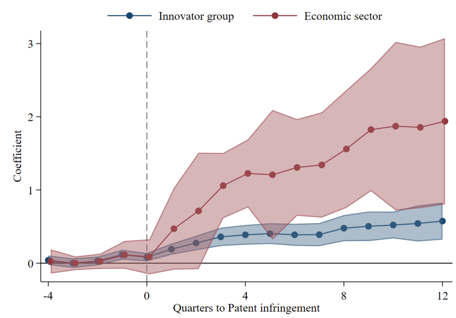
(f) Inventor Wage

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

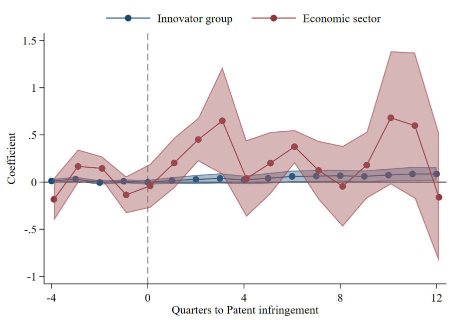
Figure 3: Dynamic Effects of Patent infringement on Innovation and Labor market outcomes II



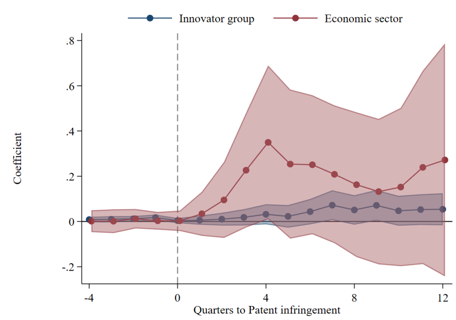
(a) Patents



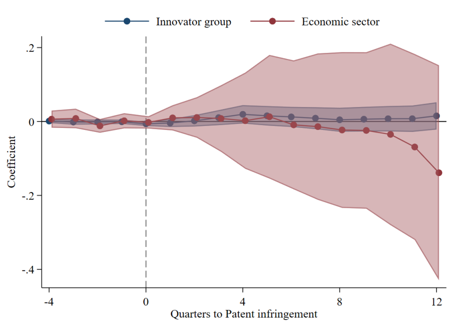
(b) Technical-augmenting Patents



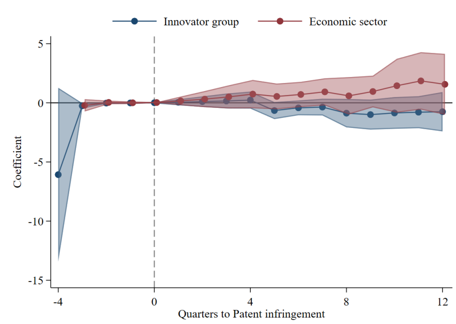
(c) Number of Inventors



(d) Number of employers



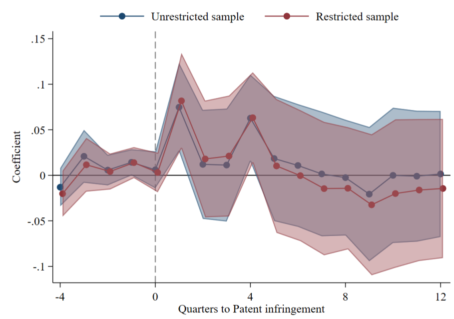
(e) Wage



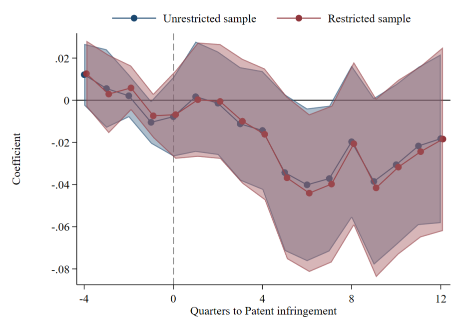
(f) Inventor Wage

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

Figure 4: Dynamic Effects of Patent infringement on Labor market outcomes by skill occupation



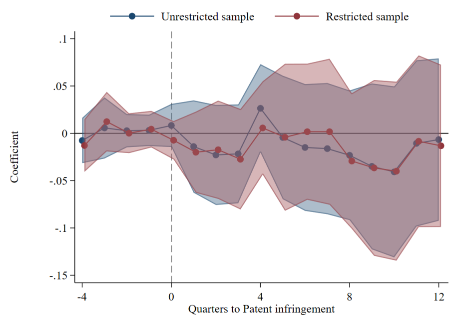
(a) Wage of High-educated employers



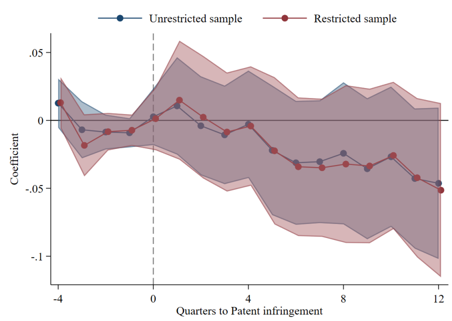
(b) Wage of Low-educated employers

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

Figure 5: Dynamic Effects of Patent infringement on Labor market outcomes by education level



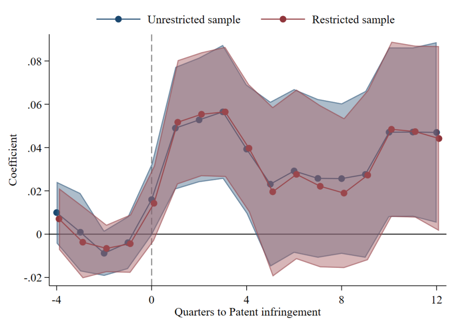
(a) Wage of high-skilled occupations



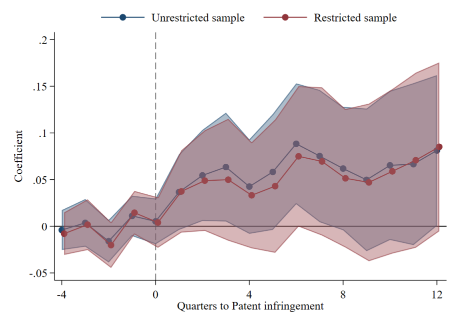
(b) Wage of Low-skilled occupations

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

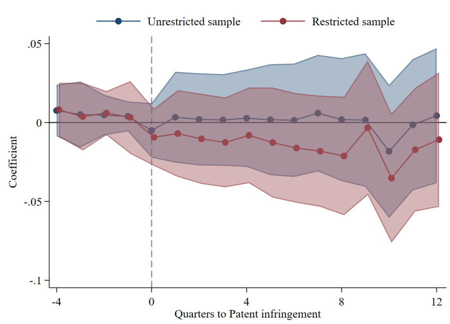
Figure 6: Dynamic Effects of Patent infringement on Gender and Race



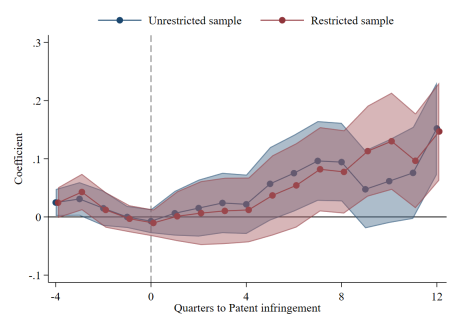
(a) Wage of man



(b) Number of man employers



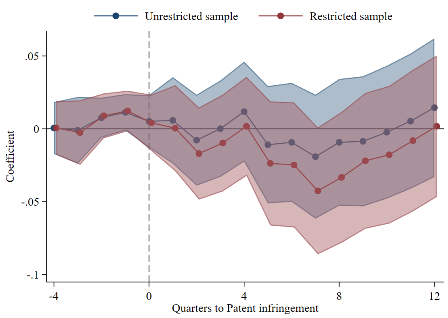
(c) Wage of woman



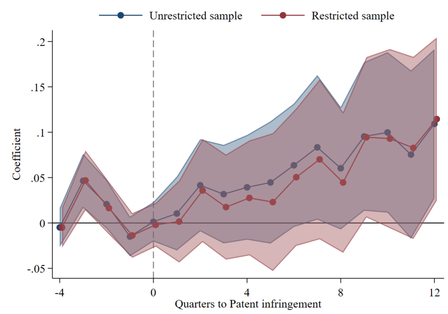
(d) Number of woman

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

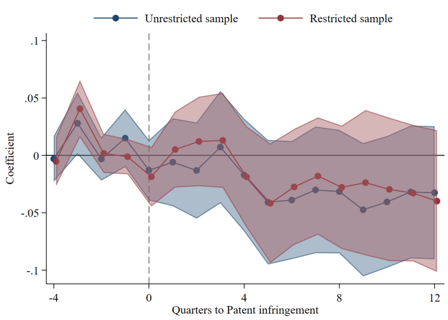
Figure 7: Dynamic Effects of Patent infringement on Race



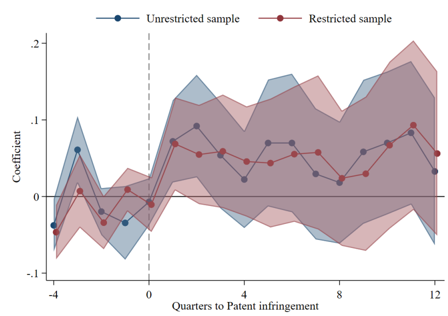
(a) Wage of white



(b) Number of white employers



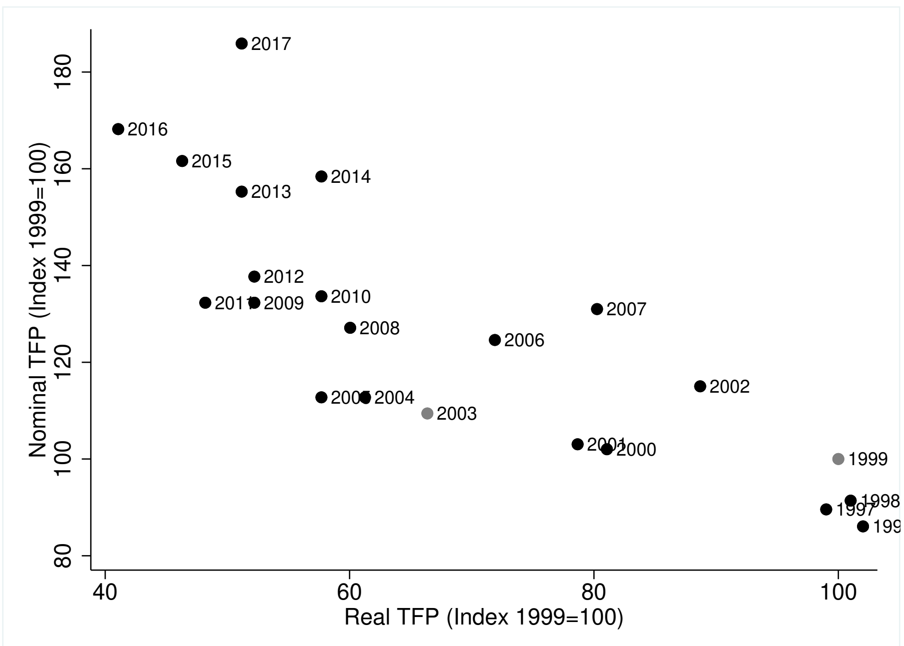
(c) Wage of non-white



(d) Number of non-whites employers

Note: This figure shows the timing of the effect of the Generic Drug law on Patent applications (panel A), on the number of inventors (panel B), on the Innovator wage (panel C), and on the Innovator wage premium (panel D). We plot coefficient estimates from equation 1 along with 95% confidence intervals, with dependent variables in growth rates. Patents application is the sum of all patent applications each month for a given firm. Inventor is the sum of all innovator of patent applications each month for a given firm.

Figure 8: Relative TFP in the Brazilian manufacture of pharmaceuticals, medicinal chemicals and botanical products



Note: Data from the PIA.

Supplementary appendix (not for publication)

A Mathematical issues

A.1 Proof of Proposition 1

Using the fact that each firm chooses its own R&D intensity to maximize its current value, that is, to maximize the right-hand side of the corresponding Bellman equation, we obtain the first-order conditions:

$$(1+\tau_1)W_{1t}z_{1t} = 0 \tag{A.1a}$$
$$(1+\tau_1)W_{2t}z_{2t} = V_{0t} - V_{2t} \tag{A.1b}$$
$$(1+\tau_0)W_{0t}z_{0t} = V_{1t} - V_{0t} \tag{A.1c}$$

Equations 10a, 10b, 10c, A.1a, A.1b, and A.1c, yield the R&D equations:

$$(1-c_t)\pi_{1t} - \frac{(1+\tau_0)W_{0t}(z_{0t})^2}{2} - (z_{2t}+h+r)(1+\tau_0)W_{0t}z_{0t} + (1+\tau_2)W_{2t}z_{0t}z_{2t} = 0$$
$$-c_t\pi_{1t} + \frac{(1+\tau_2)W_{2t}(z_{2t})^2}{2} - \frac{(1+\tau_0)W_{0t}(z_{0t})^2}{2} + (z_{0t}+h+r)(1+\tau_2)W_{2t}z_{2t} = 0$$

Resolving the above system,

$$z_{1t} = 0 \tag{A.2a}$$
$$z_{2t} = -h-r-z_{0t} + \sqrt{(-h-r-z_{0t})^2 + \frac{2c\pi_{1t} + (1+\tau_0)W_{0t}(z_{0t})^2}{(1+\tau_2)W_{2t}}} \tag{A.2b}$$
$$z_{0t} = -h-r-z_{2t}\left(1-\frac{(1+\tau_2)W_{2t}}{(1+\tau_0)W_{0t}}\right) + \sqrt{\left(-h-r-z_{2t}\left(1-\frac{(1+\tau_2)W_{2t}}{(1+\tau_0)W_{0t}}\right)\right)^2 + \frac{2(1-c)\pi_{1t}}{(1+\tau_0)W_{0t}}} \tag{A.2c}$$

Given $r=0$, the reduced form R&D is identical equations 11a, 11b and 11c. Additionally if $W_{it}=1$ and $\tau_i=0$, for all i,

$$z_{1t} = 0$$
$$z_{2t} = -h - z_{0t} + \sqrt{h^2 + (z_{0t})^2 + 2\pi_{1t}}$$
$$z_{0t} = -h + \sqrt{h^2 + 2(1-c)\pi_{1t}}$$

as in Aghion et al. (2005).

A.2 Proof of Proposition 2

Using equations A.2b and A.2c, we can obtain that

$$\begin{aligned}
\frac{\partial z_{2t}}{\partial h} &= -\left(\frac{z_{2t}}{z_{2t}+z_{0t}+h}\right) \\
&\quad + \left(\frac{(1+\tau_0)W_{0t}z_{0t}}{(z_{2t}+z_{0t}+h)\,(1+\tau_2)W_{2t}}\right)\left(\frac{\partial z_{0t}}{\partial h}\right) \\
\frac{\partial z_{0t}}{\partial h} &= -\left(\frac{z_{0t}\,(2z_{2t}+z_{0t}+h)}{\left(z_{0t}+h+\left(1-\frac{(1+\tau_2)W_{2t}}{(1+\tau_0)W_{0t}}\right)z_{2t}\right)(z_{0t}+h+z_{2t})+\frac{(1+\tau_2)W_{2t}z_{dot}^2}{(1+\tau_0)W_{0t}}}\right).
\end{aligned}$$

Since

$$(1+\tau_0)W_{0t} > (1+\tau_2)W_{2t},$$

z_{0t} and z_{2t} are decreasing in h as in proposition 2.

For equation 12, we obtain that

$$\frac{\partial I_{dt}}{\partial h} = \left[\frac{2}{2z_{0t}+z_{2t}}\right]^2\left[2z_{0t}^2\left(\frac{\partial z_{2t}}{\partial h}\right)+z_{2t}^2\left(\frac{\partial z_{0t}}{\partial h}\right)\right] \tag{A.4}$$

There is a negative effect on the aggregate innovation rate and the aggregate output when domestic economic is a high-friction economy. Thus, Control price induces a slowdown in destructive creative consequences.

B Data details and measurement issues

Table B.1: TOP 20 Patent applications by Technological group and Country-origin in Brazil

	Country-origin			
International Patent Classification (IPC)	Foreign	Domestic	Total	Freq
Medical or veterinary science; hygiene	208,017	27,383	235,400	18.70
Organic chemistry	118,908	2,511	121,419	9.65
Electric communication technique	49,611	5,695	55,306	4.39
Organic macromolecular compounds	49,085	2,981	52,066	4.14
Agriculture; forestry; animal husbandry	35,822	12,948	48,770	3.87
Biochemistry; beer; spirits; wine; vine	36,336	3,485	39,821	3.16
Conveying; packing; storing; handling	22,722	16,944	39,666	3.15
Measuring; testing	28,341	7,471	35,812	2.84
Engineering elements or units; general	24,306	6,834	31,140	2.47
Physical or chemical processes or appar	26,608	4,13	30,738	2.44
Vehicles in general	20,987	9,645	30,632	2.43
Computing; calculating; counting	23,183	6,273	29,456	2.34
Basic electric elements	22,353	4,617	26,970	2.14
Foods or foodstuffs; their treatment, n	19,698	5,583	25,281	2.01
Furniture; domestic articles or applian	6,416	18,121	24,537	1.95
Dyes; paints; polishes; natural resins;	17,362	2,076	19,438	1.54
Working of plastics; working of substan	14,415	2,717	17,132	1.36
Earth or rock drilling; mining	15,729	1,015	16,744	1.33
Generation, conversion, or distribution	11,359	4,081	15,440	1.23
Petroleum, gas or coke industries; tech	12,523	1,884	14,407	1.14

Note: Data from BADEPI. Period 1997m1-2017m12.

C Additional tables and figures

Table C.1: Comparing firms between and within groups over predetermined period

Dependent Variables	Firms in the Pharmaceutical sector × Firms in the Non-Pharmaceutical sector (1)	Innovators firms in the Pharmaceutical sector × Non-Innovators firms in the Pharmaceutical sector (2)
Wage (log)	0.386***	0.150*
	(0.017)	(0.089)
Wage of employers in high-skilled occupations (log)	0.368***	0,066
	(0.031)	(0.104)
Wage of high-educated employers (log)	0.459***	0,132
	(0.029)	(0.099)
Number of employers (log)	1.727***	0,413
	(0.066)	(0.321)
Share of employers in high-skilled occupations	-0.061***	0,011
	(0.008)	(0.014)
Share of high-educated employers	-0.058***	0,009
	(0.008)	(0.023)
Patent applications (log)		0,202
		(0.291)
Technical-augmenting patent applications (log)		0,132
		(0.299)
Innovator Wage (log)		
Number of Inventors (log)		0,013
		(0.081)
Firm FE	✓	✓
Sector#City#Time FE	✓	✓
Seasonal adjustment	✓	✓
Period covered 1996m1-1999m1	✓	✓
Clustered at the firm-month level	✓	✓

Note: Focusing 1996m1-1999m1 period, column (1) report the estimated difference between firms in the Pharmaceutical sector and firms in the Non-pharmaceutical sector. Column (2) report the estimated difference between innovator firms in the Pharmaceutical sector (Treated group) and Non-innovators firms in the Pharmaceutical sector (Control group). Estimates of the linear estimation including a dummy for predetermined innovator group. Clustered at the sector-city level, standard errors are reported in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.2: Effect of Patent infringement with Predetermined covariates

Dependent Variables	Pharmaceutical Innovators × Non-Pharmaceutical Innovators			
	(1)	(2)	(3)	(4)
Patents (log)	0.157***	0.139***	0.066**	0.062**
	(0.046)	(0.045)	(0.029)	(0.028)
Technical-augmenting patents (log)	0.172***	0.153***	0.084**	0.080**
	(0.051)	(0.050)	(0.035)	(0.034)
Number of Inventors (log)	-0.246***	-0.111***	-0.117***	-0.064***
	(0.027)	(0.011)	(0.019)	(0.009)
Number of Employers (log)	0.084***	0.110***	0.036***	0.041***
	(0.012)	(0.011)	(0.010)	(0.009)
Wage (log)	0.121***	0.081*	0.059**	0.043
	(0.040)	(0.042)	(0.027)	(0.028)
Innovator Wage (log)	-0.071***	-0.029***	-0.042***	-0.024***
	(0.007)	(0.004)	(0.006)	(0.003)
Firm FE	✓	✓	✓	✓
Sector#City#Month FE	✓	✓	✓	✓
Clustered at the firm-quarter level	✓	✓	✓	✓
Seasonal adjustment	✓	✓	✓	✓
Predetermined covariates		✓		✓
Period covered 199602-2015m11	✓	✓		
Period covered 199802-2003m02			✓	✓

Note: Each row-column report one estimate of the linear regression model specified in equation **??**. Pharmaceutical innovator firms are the treated group such that each firm provides a patent innovation with at least one pharmaceutical technology (IPC A61 - Medical or veterinary science or hygiene); and Non-Pharmaceutical innovators firms are control group such that each firm never provides a patent innovation for this classification. Column 1 shows estimates without predetermined covariates, vis-a-vis, column 2. Predetermined covariates include the number of employers (in the log), average work experience (in years), square of average work experience, and share of employers in skilled occupations. All estimations absorb the state-time fixed effects (a dummy for each 4-digit sector, city, and month) and the firm fixed effects (a dummy for each firm). Standard errors, clustered at the sector-city level, are reported in parentheses. The number of observations are different across estimations (further details in the appendix). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.3: Effect of Patent infringement (in terms of growth rates of the dependent variables)

Dependent Variables	Pharmaceutical Innovators × Non-Pharmaceutical Innovators			
	(1)	(2)	(3)	(4)
Patents (%)	0.157***	0.139***	0.066**	0.062**
	(0.046)	(0.045)	(0.029)	(0.028)
Technical-augmenting patents (%)	0.172***	0.153***	0.084**	0.080**
	(0.051)	(0.050)	(0.035)	(0.034)
Number of Inventors (%)	-0.246***	-0.111***	-0.117***	-0.064***
	(0.027)	(0.011)	(0.019)	(0.009)
Number of Employers (%)	0.084***	0.110***	0.036***	0.041***
	(0.012)	(0.011)	(0.010)	(0.009)
Wage (%)	0.121***	0.081*	0.059**	0.043
	(0.040)	(0.042)	(0.027)	(0.028)
Innovator Wage (%)	-0.071***	-0.029***	-0.042***	-0.024***
	(0.007)	(0.004)	(0.006)	(0.003)
Firm FE	✓	✓	✓	✓
Sector#City#Month FE	✓	✓	✓	✓
Clustered at the firm-quarter level	✓	✓	✓	✓
Seasonal adjustment	✓	✓	✓	✓
Covariates		✓		✓
Period covered 199602-2015m11	✓	✓		
Period covered 199802-2003m02			✓	✓

Note: Each row-column report one estimate of the linear regression model specified in equation **??**. Pharmaceutical innovator firms are the treated group such that each firm provides a patent innovation with at least one pharmaceutical technology (IPC A61 - Medical or veterinary science or hygiene); and Non-Pharmaceutical innovators firms are control group such that each firm never provides a patent innovation for this classification. Column 1 shows estimates without predetermined covariates, vis-a-vis, column 2. Predetermined covariates include the number of employers (in the log), average work experience (in years), square of average work experience, and share of employers in skilled occupations. All estimations absorb the state-time fixed effects (a dummy for each 4-digit sector, city, and month) and the firm fixed effects (a dummy for each firm). Standard errors, clustered at the sector-city level, are reported in parentheses. The number of observations are different across estimations (further details in the appendix). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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