Gains from Patent Protection - Evidence from India

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Abstract

This paper uses the implementation of a TRIPs compliant patent regime in India to study the effect of stronger intellectual property rights (IPR) on innovation and market power. Exploiting cross-industry variation in the importance of patents, we find that the reform led to more patent applications and higher investment in research and development. We also estimate an increase in average firm-product level markups which is, however, mostly driven by lower marginal costs, not higher prices. Our results indicate that costs decline post reform as a consequence of process innovations and output expansion in industries with scale economies.

JEL codes: L10, O30, O31, O00, D22

Keywords: Intellectual property rights, innovation, markups, patents

1 Introduction

There has been a long-standing interest in the effects of intellectual property rights (IPR) (Boldrin and Levine, 2013) on innovation and market power. The reward theory of patents argues that the prospect of monopoly-profits from invention would encourage firms to invest in research and development (R&D) (Arrow, 1962). Further, the publication of patents could promote the diffusion of ideas. However, strong patents and the threat of infringement could hinder follow-on innovation (Williams, 2013). The exclusive rights conferred to owners of patents may also decrease efficiency due to higher prices and markups. Thus, the net gain from stronger IPR is theoretically ambiguous, and this paper aims to contribute to this question by bringing empirical evidence from India.

As a member state of the WTO, India was obliged to move towards a stronger patent regime in the late 1990s in compliance with TRIPS. The adoption of the reform was met with staunch opposition in the Indian Parliament and created widespread uncertainty about the policy change. Thus, the adoption of reforms for pharmaceuticals and chemicals in 2000, and all other industries in 2003 came rather unexpectedly, and can be regarded as a natural experiment. In this paper, we exploit this source of exogenous variation to estimate the effects of stronger IPR on innovation, markups and other outcome variables.

To identify the effect of the reform, we exploit variation in the extent to which product groups rely on patents as an appropriating mechanism. We use data on Indian firms from CMIE prowess and find that stronger IPR protection leads to an increase in R&D spending and the number of patent applications in industries that are more exposed to the reform. The effect on innovative investment persists and becomes larger with time. The results are robust to accounting for other policy changes introduced in India during the 1990s-2000s, using alternate measures of exposure to the reform, and accounting for industry trends.

To study the effect on market power, we follow De Loecker et al. (2016) to estimate product-level markups, and use the price information in Prowess to estimate marginal costs. We find that the reform led to an increase in average markups of the most exposed industries, however the increase was driven by a decline in marginal costs and not an increase in prices. We present evidence for two possible explanations for the drop in marginal costs. First, in industries with high returns to scale, the reform leads on average to an increase in the sales of products most exposed to the reform, and this could explain the drop in marginal costs. Second, we find that firms file more process patents as compared to product patents after the reform.

A number of empirical studies have tried to estimate the effects of IPR on R&D and other outcomes such as prices.[1] Although fifteen years have passed since TRIPS compliant patent reform was adopted in India, there continues to be little evidence on the impact of the reform in India. The existing literature has focused on studying the effects of the reform in the pharmaceutical sector since the reform was particularly controversial for this industry (Duggan et al., 2016; Chadha, 2009). This paper contributes to this literature by bringing cross-industry evidence on the gains from adopting a stronger IPR regime in India, an important developing country.

The rest of the paper is structured as follows. Section 2 discusses the institutional background and India's patent reform. Section 3 describes the panel data, and the measure of exposure to reform used in the baseline. Section 4 presents the empirical strategy and sections 5 and 6 present the results for investment in innovative activity and market power. Section 7 concludes.

2 The TRIPS reform

Prior to India joining the WTO in 1995, India had a weak patent law governed by the India Patent Act, 1970 (Reddy T. and Chandrashekaran, 2017). Besides restrictions on product patents for substances intended for use as pharmaceuticals, food and chemicals, and those prepared or produced by chemical processes, process patents for such technologies were also subject to a system of licenses of right which effectively reduced the period of market exclusivity for patentees to three years. These provisions had wide support in the Indian parliament.

During the Uruguay round of GATT negotiations, developed nations proposed to link intellectual property rights (IPRs) to trade through the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). While developing countries showed resistance initially, they buckled under pressure of trade sanctions. Moreover, India ran into a balance-of-payment crisis by 1991, and IMF conditioned its assistance on India opening its economy and becoming a member of the World Trade Organisation (WTO). India signed the Marrakesh Agreement in 1994 to become part of the WTO and consequently agreed to introduce IPR reforms to comply with TRIPS over a ten-year period (1995-2005).

To comply with the immediate obligations under TRIPS, the government introduced the Patents (Amendement) Bill, 1995, but the bill lapsed due to strong opposition in parliament. After several years of uncertainty, and complaints by the US and European Commission at the Dispute Settlement Body (DSB) of the WTO against India for not abiding by TRIPS, a change in government paved

[1] See the overview of related literature in Bryan and Williams (2021) and Budish et al. (2016). For recent contribution on the effect of IPR on R&D expenditure see Arque-Castells (2022), and for its effect on prices see de Rassenfosse and Zhou (2020)

the path for India implementing The Patents (Amendement) Act, 1999. The amendment granted patent-like monopoly rights for product patents in pharmaceuticals, drugs and agrochemicals. The Act came into effect from 26th March 1999, and hence, we define financial year 1999-2000 as the first year of patent reform for pharmaceuticals and chemicals.

The second set of reforms were were deliberated over by a joint parliamentary committee between 1999 and 2002, and came into effect with the Patents (Second Amendement) Act, 2002. The reforms were applicable to all industries, and included an increase in the term of a patent from 14 to 20 years, a new definition for 'invention', deletion of royalty limit for licensing process patents. We define financial year 2002-2003 as the first year of reform for all industries except pharmaceuticals and chemicals.

3 Data

3.1 Firm level data

Our main data source is the Prowess database compiled by the Centre for Monitoring of the Indian Economy (CMIE). Prowess is a panel dataset of Indian publicly listed and private firms across all sectors since 1989. It includes data from company balance sheets and profit and loss accounts. The sample of firms in Prowess accounts for more than 70% of the industrial output of the organized sector and 75% of corporate taxes and 95% of excise taxes collected by the government (see, e,g, Topalova and Khandelwal, 2011). Prowess also records details of the products sold by firms in the manufacturing sector, including information on quantities and values of sales. For the purpose of understanding the impact of the patent reform, we use data from financial year 1995 to 2010, and focus on manufacturing firms for which we have product level information.

To study the innovative performance of Indian firms, we use information on the current and capital expenditure on R&D directly from firms' financial accounts. We also create a measure of the number of patent applications filed by firms at the Indian Patent Office. We match the applicant names in patent applications with firm names in Prowess. Details for the matching are discussed in Appendix B. Table 1 shows summary statistics of R&D expenditure and patent applications in our data.

To study the effect of patenting on market power, we estimate markups, and marginal costs following the methodology introduced by De Loecker et al. (2016). This method uses a production function approach for multi-product firms. Under cost minimization, it can be shown that the markup of a product, defined as price divided by marginal costs, equals the input-output elasticity of material inputs multiplied by the ratio of revenue to material expenditures. The method exploits quantity and price information at the product level to separate physical productivity from revenue based productivity and controls for unobserved quality differences using a control function that is based on market share and output prices. The estimation routine recovers an estimate of markups and marginal costs for each product sold by a firm in a year. We use a translog production function in the estimation of markups in the baseline. Table 1 shows the summary statistics of estimated markups in our data.[2]

3.2 Exposure to reform

Industry surveys shows that the use of patents to safeguard inventions varies substantially across industries (Cohen et al., 2000; Levin et al., 1987). Since the patent reform in India, especially from 2002 affected all industries, we exploit variation in the reliance on patents as a mechanism of appropriation. In the baseline, we borrow a measure of patent intensity at 4-digit industry level from EPO (2013). This study is a joint statistical effort made by the European Patent Office (EPO) and the Office for Harmonization in the Internal Market (OHIM) where they match patent data from PATSTAT with the commercial database ORBIS which contains industry classification for more than 20 million European firms. Using the matched data, they measure relative patent intensity as the total number of granted patents assigned to an industry divided by total employment for that industry, leading to an indicator of patent numbers per 1,000 employees.[3]

Assuming that the reliance on patenting as an appropriating mechanism is an intrinsic character of an industry, irrespective of geographical location, we use this measure to define exposure to the reform of Indian firms. We merge the patent intensity measure defined for 4-digit NACE industries with firm-products in Prowess data. First, we define a five digit NIC (National Industrial Classification) code for each 12-digit product code reported in Prowess. Then, we use a concordance between NACE 4-digit and NIC 4-digit to merge the EPO-OHIM patent intensity measure. Finally, we take the average of the values for each NIC four digit industry code. This is our baseline measure of exposure to the reform.

To measure exposure to the reform at the firm-level, we use a sales-weighted measure of patent

[2]We check the robustness of our results to accounting for firm R&D investment and patent applications filed in the productivity markov process.

[3]The report shows the value of patent intensity for industries with above average patent intensity. We impute the lower bound of this value for industries that have a below average measure of patent intensity. We check the robustness of our result with using zero as the value of patent intensity for industries with below average patent intensity.

intensity for the product-mix of firms prior to 1999 as follows:

$$PatentIntensity_i = \sum_{t=1995}^{1999} \frac{Sales_{ijt} * PatentIntensity_j}{\sum Sales_{ijt}} \tag{1}$$

where i is the firm, j is the 4-digit industry, and t is the financial year.

4 Empirical Strategy

We evaluate the impact of the patent reform on firm innovative activity as follows:

$$A(y_{it}) = \beta Post_{jt} * PatentIntensity_i + \lambda_t + \lambda_i + \epsilon_{it} \tag{2}$$

where y_{it} is the outcome of interest. We use the inverse hyperbolic sine of both R&D expenditures and the number of patent applications filed by a firm i in year t. $Post_{jt}$ is a dummy equal to one from 2000 onwards for firms whose main industry classification is pharmaceuticals and chemicals, and equal to one for all other industries from 2003 onwards. $PatentIntensity_i$ is a time-invariant firm-level measure of the exposure to reform as defined in Equation 1. We include firm fixed effects (λ_i) to control for time-invariant differences between firms, and year fixed effects (λ_t) to control for macroeconomic changes that could affect all firms. Our coefficient of interest is β which estimates how the innovative activity of firms changes post reform for a one percent change in the exposure to the patent reform. We cluster the standard errors at firm level.

We study the effect of the reform on market power as follows:

$$\ln(y_{ipt}) = \beta Post_{jt} * PatentIntensity_j + \lambda_t + \lambda_{ip} + \epsilon_{ipt} \tag{3}$$

where $\ln(y_{ipt})$ is the log of markup, marginal cost, and prices of firm i, for a 12 digit product p during year t.[4] $Post_{jt}$ is a dummy equal to one from 2000 onwards for all products mapping into four-digit NIC code j that belong to pharmaceuticals and chemicals, and it is equal to one for all other products from 2003 onwards. $PatentIntensity_j$ is a time-invariant industry-level measure of the exposure to reform borrowed from EPO (2013). We include firm by product fixed effects (λ_{ip}) to control for time-invariant differences between firm-product combinations, and year fixed effects to control for macroeconomic changes that could affect all firms. Our coefficient of interest is β

[4] The markup estimation takes into account that firms report quantities sold using different units. Thus, p is essentially a product-unit combination.

which estimates the relative (approximately percent) change in y_{ipt} after the reform for a product with a patent intensity index of one. We cluster the standard errors at four-digit industry level.

5 Results: Firm-level innovative activity

Table 2 shows the baseline result. We find that our main coefficient of interest, $Post*PatentIntensity$ is positive and statistically significant for both R&D expenditure and patent applications filed at the India Patent Office. Thus, firms most exposed to the patent reform, i.e. firms selling products that rely importantly on patents as an appropriation mechanism, saw an increase in their R&D expenditure, and number of patent applications filed at the Indian Patent Office.[5]

We study the effect of the reform over time in Figure 1. Since the patent reform kicked in earlier for pharmaceuticals and chemical sectors, we define year 2000 as event year 0 for these sectors. For all other industries, we define 2003 as event year 0. We then interact $PatentIntensity_i$ with each event year, and plot the coefficients and 95% confidence intervals in Figure 1. First, we find that prior to the reform there is no significant difference in the R&D expenditure and patent applications of firms more exposed to the reform. Thus as argued in Section 2 firms did not seem to have anticipated that the patent reform was going to be implemented after India became part of WTO in 1995.[6] Second, the effect of the reform on the innovative activity of firms most exposed to the reform gradually increases over time, and the effect persists for at least eight years after the reform.

5.1 Robustness tests and extensions

Controlling for other major reforms in India

While the empirical strategy uses variation in the reliance on patenting across four-digit industries to identify the effect of the reform, a concern could be that the more patent-intensive industries were also affected by other major reforms that were initiated in India since the 1990s. To allay this concern, we control for policy changes at the industry level, including delicensing (Aghion et al., 2008), trade liberalisation (Topalova and Khandelwal, 2011), deregulation of foreign ownership caps (Ali and Stiebale, 2021), and increase of R&D tax credits (Ivus et al., 2021). Results in in Table 6 show that the effect of the reform on firm innovative activity remains robust to controlling for

[5]The result is not driven by the intensive margin as there is also a statistically significant increase in the number of firms reporting positive R&D expenditure and those filing patent applications.

[6]We study the effect of the reform for the full data without pharmaceuticals and chemicals, and do not find any pre-trends for this sample too, even between 1999 and 2002. The results thus show that there was widespread uncertainty regarding the passing of the reforms, and firms did not increase their expenses on R&D in anticipation.

these policy changes.

Measuring effect on capital investment

A potential concern with our identification strategy is that firms most exposed to the reform happened to operate in the most dynamic, high-growth sectors. We therefore study the effect on investment in capital goods using equation 2. Results are reported in Table 7. We find that the coefficient on $Post * PatentIntensity$ is negative and significant at the ten-percent level. Thus, firms most exposed to the reform don't invest more in capital goods post reform. Thus, in line with the intention of the reform, the effect seems to be concentrated on innovative activity, and not all kinds of investment.

Alternate measure of exposure to the reform

In Table 8, we check the robustness of the result to using an alternate measure of patent intensity across industries. Cohen et al. (2000) surveyed US manufacturing firms during 1994 and provide a measure of the percentage of firms applying for patents in a given industry. We estimate exposure to the reform at firm level using equation 1, and estimate the effect of the reform using equation 2. We find that $Post * PatentIntensity$ for R&D expenditure and number of patent applications remains positive and significant with the survey measure.[7]

Controlling for industry trends

In Figure 3, we repeat the baseline regression (equation 2) but include industry-year fixed effects to control for any trend growth in industry groups. We use 13 aggregated industry groups. Even with this demanding specification, the results remain similar, thus allaying the concern that underlying industry dynamics led to the increase in innovative activity of firms affected by the reform.

Heterogeneity results

In Table 9, we split our sample into four groups based on the pre-reform size of a firm within a four-digit NIC group. In panel A, we find that the effect of the reform on R&D expenditures is monotonically increasingly in firm size. Thus, while the smallest firms do not significantly increase R&D spending post reform, the effect is positive and significant for firms in the second, third and fourth quartile. The effect on R&D expenditure of the largest firms (column 4) is almost double the effect on medium sized firms (column 2) In panel B, we find a similar pattern for patenting activity such that the coefficient on $Post * PatentIntensity$ is increasing from the lowest to the

[7] Cohen et al. (2000) provide information for only 41 four-digit ISIC Revision 3.1 industry groups. We assume a value of zero for all the other industry groups in mapping the measure to four-digit NIC industry groups.

highest quartile.

In Table 10, we use the classification of differentiated and homogeneous products proposed by Rauch (1999) to split the sample of firms. We define a firm as 'differentiated' if more than 50% of its product mix classifies as differentiated products. We find that the effect of the reform on firm innovative activity is stronger for firms producing differentiated products as compared to firms producing homogeneous products.

6 Results: Change in market power

Theoretically, the key disadvantage of stronger patent rights is that they allow inventors to charge a higher price markup for the duration of the patent, leading to efficiency losses in the economy. As discussed in section 3, we observe prices and quantities of products sold by firms, and following De Loecker et al. (2016) we are able to estimate markups and marginal costs. We estimate the effect of the patent reform on product markups, marginal costs, and prices using equation 3.

Table 3 shows the results. In column (1), we see that post reform, the average markup in product groups most exposed to the reform increased. Column (2) shows that the increase in markups is not a due to higher prices on average, but lower marginal costs (column 3). Thus, on average firms become more efficient at producing goods that are more exposed to the reform, and do not pass the efficiency gains on to consumers in the form of lower prices.[8]

We study the effect on markups, marginal costs, and prices over time in Figure 2. Again, since the patent reform kicked in earlier for pharmaceuticals and chemical sector, we define year 2000 as event year 0 for these sectors. For all other industries, we define 2003 as event year 0. We then interact $PatentIntensity_j$ with each event year, and plot the coefficients and 95% confidence intervals. We do not find any significant differences by exposure to reform prior to the onset of the reform. However after the reform was implemented, there is an increase in average markups in product groups exposed to the reform. In the initial years after the reform, there is an increase in prices for products groups exposed to the reform, however the price increase does not persist. Marginal costs start falling several years after the reform and contribute to the rise in markups.

[8]The results are robust to modifications in the estimation of markups, such as accounting for R&D expenditure and patent applications in the productivity markov process, and to also using markups estimated for a Cobb-Douglas production function.

6.1 Discussion

In this section we explore mechanisms that could explain the fall in marginal costs after the patent reform in product groups most exposed to the reform. We find evidence for two channels.

First, the decline in marginal costs could be an outcome of higher sales and lower cost of production at the margin. However, not all industries have an increasing returns to scale production function. We calculate the average returns to scale within a four-digit NIC product group, and split the baseline sample by the median value of returns to scale. Table 4 shows the result of estimating equation 3 for sales, markups, marginal costs, and prices as the dependent variables for the sample of products with below median returns to scale (Columns 1-4), and for the sample of products with an above median returns to scale (Columns 5-8). We find that there is an increase in average amount of quantity sold (column 5) in product groups with scale economies. In tandem, there is a decline in marginal costs (Column 8), and an increase in markups (Column 6). This mechanism is missing in products group without scale economies. As seen in Column (3), in product groups without scale economies, there is an increase in prices on average, and the effect on markups (column 2) is not precisely estimated.

A second explanation for the decline in marginal costs could be that firms undertake important process innovation. We categorise patents filed by firms in Prowess into three groups: (a) patent applications with largely process innovation related claims,(b) those with product innovation related claims, and (c) those that include claims for both product and process innovation. We follow Banholzer et al. (2019) and search for keywords related to process versus product patents in the abstract of the patent. As shown in Table 5, we find that the reform had a positive and significant effect on all kinds of patents, but the effect was economically largest on the number of process patents (column 1) when compared to the effect on the number of product patents (column 2) and those that have both product and process innovation claims (column 3).

7 Conclusion

This paper brings evidence on the effect of stronger intellectual property rights on investment in innovation and market power. It contributes to the long standing debate of whether government-granted monopoly rights in the form of patents promote technological progress and whether there are important side effects.

We exploit data from India, an important developing country, where the adoption of TRIPS compliant patent reforms offers a quasi-natural experiment to study the question at hand. To identify the effect of the reform, we exploit variation in the extent to which product groups rely on patents to protect innovations. We find that stronger IPR protection leads to an increase in expenditure on R&D, and in the number of patent applications in industries that are more exposed to the reform. There is an increase in average markups for the most exposed industries. However, the increase is driven by a decline in marginal costs and not an increase in prices. Results suggest that the decline in marginal costs is partly explained by higher sales and consequent economies of scale, and a larger increase in process innovations as compared to product innovations. The paper thus suggests that—at least in the case of India—stronger patent rights have fostered innovation with limited negative consequences.

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Table 1: Summary statistics

Variable	Mean	Median	SD	Observed
Firm-level data				
R&D expenditure	16.45	0.00	213.39	40997
Patent applications	0.23	0.00	3.68	40997
IPR Intensive	2.95	1.57	3.78	40997
Product-level data				
Markup	6.40	1.40	55.35	75480

8 Tables and Figures

Table 2: Innovative activity: Baseline

Dependent Variables:	R&D (Inv Hyp Sine)	Patents (Inv Hyp Sine)
Model:	(1)	(2)
Variables		
Post	-0.2015***	-0.1474***
	(0.0468)	(0.0256)
Post * Patent Intensity	0.0386***	0.0223***
	(0.0077)	(0.0038)
Fixed-effects		
Firm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	40,997	40,997
R^2	0.80853	0.53370

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Market power: Baseline

Dependent Variables:	Log of markup	Log of prices	Log of marginal cost
Model:	(1)	(2)	(3)
Variables			
Post	-0.0533	0.0117	0.0650
	(0.0536)	(0.0384)	(0.0692)
Post * Patent Intensity	0.0107*	-0.0028	-0.0135***
	(0.0055)	(0.0044)	(0.0045)
Fixed-effects			
Firm-Product-Unit	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	75,480	75,480	75,480
R^2	0.77841	0.96920	0.93029

Clustered (pnic4) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 1: Innovative activity: Event-time plot

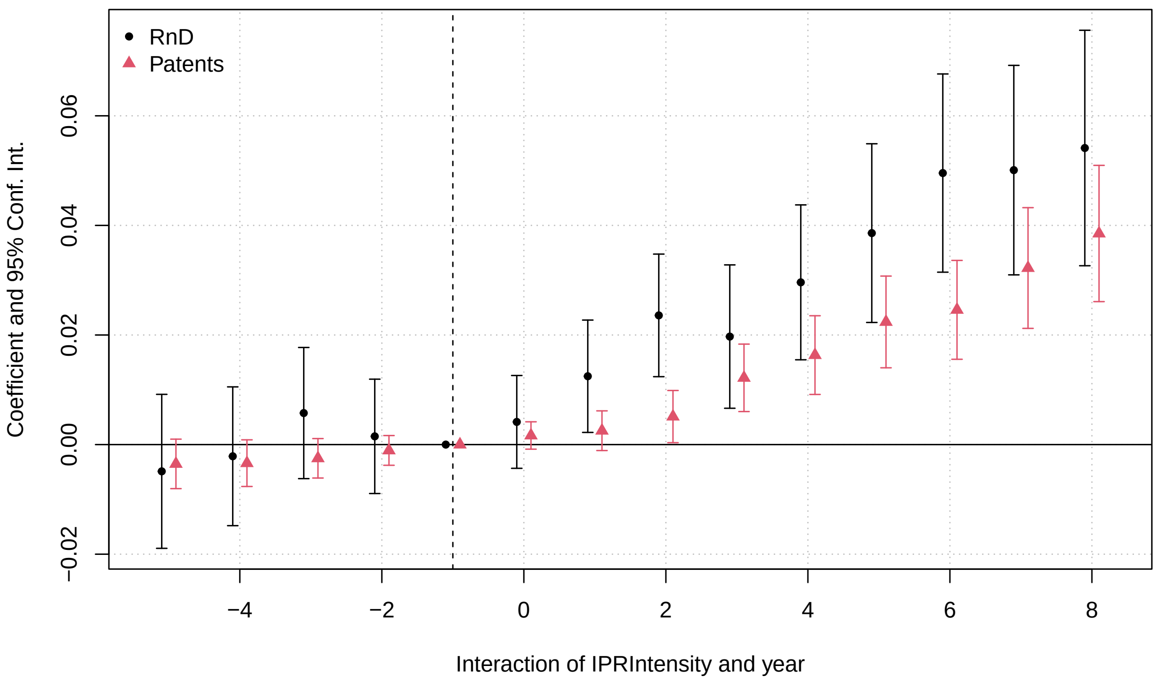


Figure 2: Market power : Event-time plot

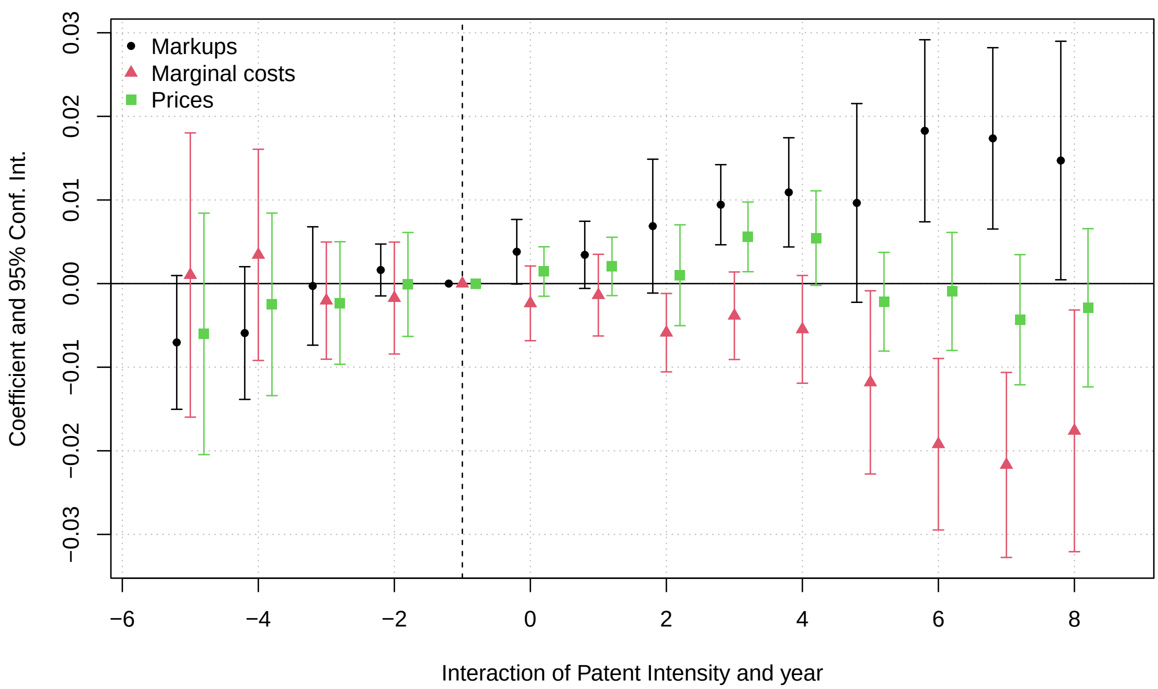


Table 4: Market power: Sample split by scale economies

Dependent Variables (Log of):	quantity sold	markup	prices	marginal cost	quantity sold	markup	prices	marginal cost
		No scale economies				Scale economies		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Post	0.0390	-0.0416	-0.0224	0.0192	-0.0034	-0.0792	-0.0145	0.0648
	(0.0398)	(0.0585)	(0.0350)	(0.0659)	(0.0417)	(0.0495)	(0.0471)	(0.0566)
Post * Patent Intensity	-0.0030	0.0080	0.0107***	0.0027	0.0090*	0.0137**	0.0004	-0.0133**
	(0.0049)	(0.0049)	(0.0036)	(0.0063)	(0.0050)	(0.0069)	(0.0086)	(0.0056)
Fixed-effects								
Firm-Product-Unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	36,390	36,390	36,390	36,390	39,090	39,090	39,090	39,090
R^2	0.95977	0.81097	0.98313	0.94997	0.94672	0.80874	0.97132	0.93651

Clustered (pnic4) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

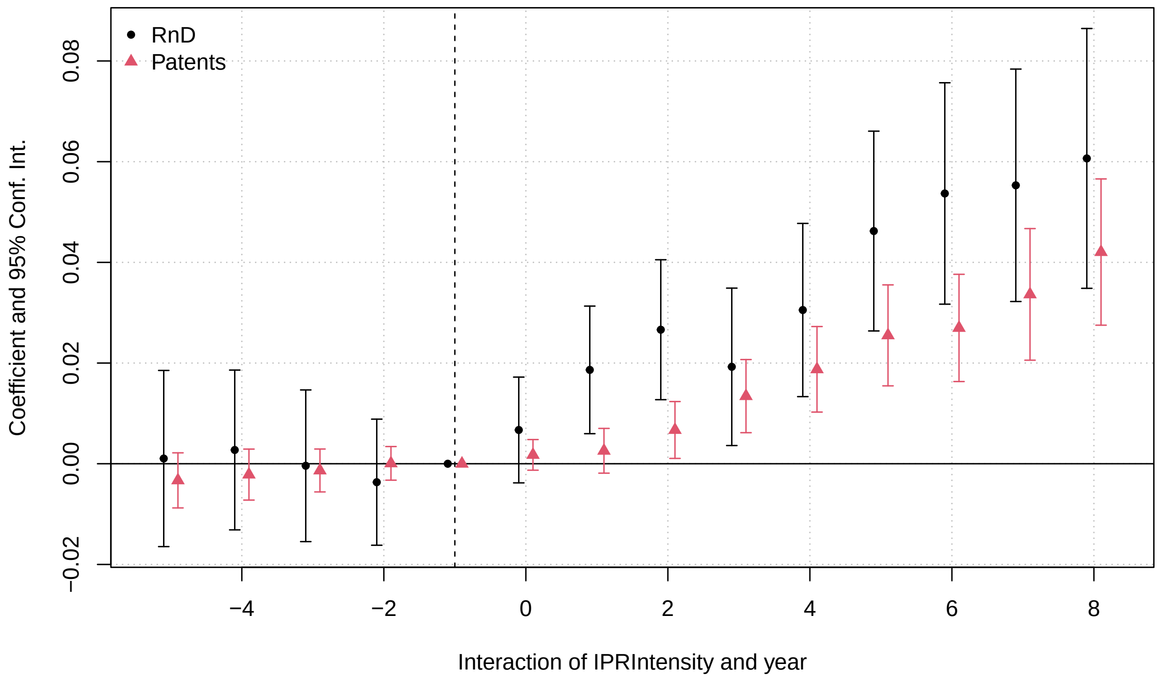
Table 5: Product versus process patents

Dependent Variables:	Process patents	Product patents	Product + Process patents
Model:	(1)	(2)	(3)
Variables			
Post	-0.1057***	-0.0403***	-0.0672***
	(0.0206)	(0.0112)	(0.0143)
Post * Patent Intensity	0.0138***	0.0067***	0.0106***
	(0.0027)	(0.0015)	(0.0021)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	40,997	40,997	40,997
R^2	0.46383	0.43917	0.44508

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 3: Innovative activity: With industry-year FE



A Appendix: Additional tables

Table 6: Innovative activity: With other reforms

Dependent Variables:	R&D (Inv Hyp Sine)	Patents (Inv Hyp Sine)
Model:	(1)	(2)
Variables		
Post	-0.0573	-0.0340***
	(0.0391)	(0.0109)
Post * Patent Intensity	0.0228**	0.0103***
	(0.0092)	(0.0027)
Input tariff	-0.8153***	-0.0891
	(0.2833)	(0.1003)
Output tariff	0.0059	-0.0123
	(0.0858)	(0.0225)
FDI reform	0.1160	-0.0384**
	(0.0720)	(0.0185)
Delicensing	0.1510*	0.0526
	(0.0834)	(0.0321)
R&D tax credit	-0.0008	-0.0001
	(0.0012)	(0.0004)
Fixed-effects		
Firm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	38,671	38,671
R^2	0.80703	0.49269
Within R^2	0.00314	0.00298

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Firm capital investment

Dependent Variable:	Investment
Model:	(1)
Variables	
Post	0.0115
	(0.0173)
Post * Patent Intensity	-0.0057*
	(0.0031)
Fixed-effects	
Firm	Yes
Year	Yes
Fit statistics	
Observations	34,666
R^2	0.21759

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Alternate measure of exposure to the reform

Dependent Variables:	R&D (Inv Hyp Sine)	Patents (Inv Hyp Sine)
Model:	(1)	(2)
Variables		
Post	-0.8752***	-0.3517***
	(0.1171)	(0.0527)
Post × Patent Intensity (Cohen)	0.0126***	0.0044***
	(0.0017)	(0.0007)
Fixed-effects		
Firm	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	40,109	40,109
R^2	0.80823	0.52793

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Innovative activity: By firm size

Panel A				
Dependent Variable:	R&D (Inv Hyp Sine)			
	Small	Medium	Large	Huge
Model:	(1)	(2)	(3)	(4)
Variables				
Post	-0.0089	-0.1773**	-0.2362***	-0.2986***
	(0.0468)	(0.0848)	(0.0905)	(0.1007)
Post * Patent Intensity	0.0042	0.0312**	0.0481***	0.0580***
	(0.0071)	(0.0135)	(0.0124)	(0.0189)

Panel B				
Dependent Variable:	Patents (Inv Hyp Sine)			
	Small	Medium	Large	Huge
Model:	(1)	(2)	(3)	(4)
Variables				
Post	-0.0281**	-0.1063**	-0.0999***	-0.2861***
	(0.0137)	(0.0457)	(0.0350)	(0.0622)
Post * Patent Intensity	0.0014	0.0174**	0.0147***	0.0464***
	(0.0009)	(0.0069)	(0.0048)	(0.0092)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	7,680	9,446	10,970	12,901
R^2	0.25319	0.58122	0.43195	0.55478

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Innovative activity: By degree of product differentiation

Dependent Variables:	R&D (Inv Hyp Sine)	Patents (Inv Hyp Sine)	R&D (Inv Hyp Sine)	Patents (Inv Hyp Sine)
	Differentiated		Homogeneous	
Model:	(1)	(2)	(3)	(4)
Variables				
Post	-0.3524***	-0.2769***	-0.0474	-0.0413***
	(0.0874)	(0.0538)	(0.0554)	(0.0155)
Post * Patent Intensity	0.0377***	0.0249***	0.0100	0.0112**
	(0.0091)	(0.0047)	(0.0162)	(0.0048)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,917	18,917	19,592	19,592
R^2	0.81316	0.55000	0.80246	0.50185

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Appendix: Patent Matching

Before matching patent applicants to Prowess firm names, we clean the strings to make them comparable. To begin with, we only work with patents where atleast one of the applicants is Indian, since Prowess is a database of Indian companies. The matching process can be affected due to spelling mistakes, special characters and redundant terms. In addition, we try to format unique company terms in a homogeneous form.

We use the Fuzzyjoin package in R to match the applicant name and firm name. The method of fuzzy matching used here is called jaro-winkler matching. It calculates a distance depending on the similarities of two strings. The higher the distance, the less similar are the strings. We specify a maximum distance of 0.1 which means only matches below this threshold are matched. Additionally, we choose a penalty factor of 0.1 which applies a subtraction to the distance if the first four letters of the string are similar. Thus more weight is placed on the first part of the string. This is done because we observe that similarities between strings are often in the initial letters. We allow for patent applicants to have multiple matches in cases where the match is not perfect.

We then manually check the matching quality for matches that are not perfectly matched. We use firm address from Prowess and applicant address of the patent to determine if the match is good or bad.