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Gains from Patent Protection: Innovation, Market Power and Cost Savings in India

Apoorva Gupta and Joel Stiebale*

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Abstract: We study the effect of stronger patent protection on innovation activities of firms and firm-product level markups. Relying on cross-industry differences in the use of patents, we exploit firm-level variation in exposure to India's patent reform. For firms more exposed to stronger patent protection, we find an increase in patenting and R&D expenditure post-reform. Additionally, we estimate an increase in firm-product level markups after the reform, driven primarily by lower marginal costs rather than higher prices. Our results indicate that process innovations and output expansion contributed to these cost-savings, and incomplete pass-through accounts for a substantial part of rising markups.

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

Keywords: Intellectual property rights, patent protection, innovation, R&D, markups, patents

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1 Introduction

There has been a long-standing interest in the effects of patent protection on firms and consumers (e.g., Boldrin and Levine, 2013; Williams, 2017). On the one hand, the reward theory of patents argues that the prospect of exclusive rights would encourage firms to invest in research and development (R&D) (Arrow, 1962).[1] On the other hand, strong patents can lead to higher market power (e.g., Bloom et al., 2019) implying negative consequences for consumer welfare, labour demand and investment incentives. Thus, the net gain from stronger patent protection is theoretically ambiguous. Existing evidence on the effects of patent protection on R&D investment is, unfortunately, rather inconclusive and often limited to very specific markets.[2] Further, we know relatively little about the impact of patent protection on market power and the underlying mechanisms.

There are several reasons why stronger patent protection may lead to greater market power, which is usually defined as the ability of firms to set prices above marginal costs. First, stronger protection of existing innovations can reduce price competition and entry, thereby increasing the market power of patent holders. Second, markups, the wedges between prices and marginal costs, might change as a consequence of innovation activities induced by patent protection. For instance, cost-reducing innovations allow firms to charge higher markups in an environment with incomplete pass-through. Alternatively, new or improved products can affect the elasticity of demand, allowing firms to increase prices relative to costs. Indeed, changes in technology are one potential driver of increasing aggregate markups as documented in recent literature (e.g., De Loecker et al., 2020; De Ridder, 2024; Miller, 2024).

In this paper, we estimate the effects of stronger patent protection, induced by India's patent amendment acts, on both innovation activities and markups of domestic firms across all manufacturing industries. To understand the underlying mechanism

[1] Further, the publication of patents could promote the diffusion of ideas. A counter argument is that strong patents and the threat of infringement could hinder follow-on innovation (Williams, 2013).

[2] See the literature surveys in Bryan and Williams (2021), Williams (2017), Budish et al. (2016).

of how stronger patent protection affects markups, we decompose markup changes into price and marginal cost changes and further study effects on output and proxies for product quality. We also analyse the effect on different types of patents that are filed after the implementation of the new patent regime, including process vs. product patents and different indicators for quality-adjusted patents.

In the wake of a balance of payment crisis in 1991, India found itself obliged to become a member state of the World Trade Organization (WTO), and consequently moved towards a stronger patent regime in the late 1990s in compliance with the Trade Related Intellectual Property Rights (TRIPS) agreement. The adoption of the reform was met with staunch opposition in the Indian Parliament and created prolonged uncertainty about the timing and nature of the policy change (Reddy and Chandrashekaran, 2017). The eventual adoption of reforms for pharmaceuticals and chemical industries in financial year 2000, and all other industries in 2003 occurred unexpectedly, and can be regarded as a natural experiment.

To study the effects of the patent reform, we source data on Indian manufacturing firms from CMIE Prowess, which along with providing accounting information, provides the registered name of the firm and the products produced by it annually. We use firm names to match patents filed at the Indian Patent Office with the firm level data, and thus obtain a measure that allows us to check if the reform had its intended effect. Information on the prices and quantities of products produced by a firm enable us to adopt the approach introduced by De Loecker et al. (2016) to estimate markups at firm-product level, and use the price information in Prowess to recover marginal costs.

For identification, we use a difference-in-difference design, where to measure exposure to the reform, we rely on the insight that there exists large variation in the extent to which industries rely on patents to protect their inventions, even within broad sectors. Using the product-mix produced by a firm prior to the reform, we obtain firm-level variation in reform exposure. Importantly, our measure of exposure to the stronger patent protection reform shows little correlation with pre-reform indicators of firm growth and other implemented reforms, most notably India's trade liberalization. Nonetheless, we use sector-year fixed effects to identify the effect of the reform by comparing firms within the same 2-digit sector, and show that our results are robust to accounting for other policy changes introduced in India during the 1990s and 2000s, to controlling for several time-varying firm characteristics, unit-specific pre-trends and to using alternate measures of exposure to the reform.

We first analyse the effect of the patent reform on patenting and innovation investment. We find that stronger patent protection was associated with an increase in both the number of patents filed by a firm, and the number of firms that patent. Additionally, firms most exposed to the reform increased their R&D expenses, suggesting that the reform increased the private returns from investing in innovation. Analysis using an event-study approach indicates that firms did not anticipate the reform, and that post reform, the growth of patenting and R&D investment gradually increased and persisted for several years. Moreover, employing three indicators of patent quality—the number of patents renewed by a firm, the number of inventors per patent, and the number of patents filed internationally—shows that the surge in patent quantity was also accompanied by an increase in high-quality patents.

Next, we analyse the effect on market power, and find that the reform led to an increase in average markups, both at the firm-product level and firm-level. The increase, however, was mainly driven by a decline in marginal costs, while average prices did not change significantly. Accounting for time-heterogeneous treatment effects using an event-study framework shows a gradual and persistent increase in markups a few years after the implementation of the reform, again driven by a decline in marginal costs.

There are several potential explanations for why marginal cost reductions do not translate into lower prices. First, with imperfect competition, it is likely that the pass-through of cost savings to prices is incomplete. Further, an increase in (perceived) product quality or a reduction in competition through stronger patents may increase prices conditional on marginal costs. We only find small and statistically insignificant changes in proxies for product quality and markup changes *conditional on changes in marginal cost*, suggesting that a large part of the increase in markups is due to incomplete pass-through of cost savings.

We present evidence for two possible explanations for the drop in marginal costs. First, disaggregating patents into process and product patents, we estimate a disproportionate increase in process patents after the reform. Given that process patents are often geared towards developing cost-saving processes, a surge in such patents explains why marginal costs would decline after the reform. Second, we find that, in industries with scale economies, exposure to stronger patent protection was associated with an increase in output and relatively large cost reductions.

A number of empirical studies have tried to estimate the effects of patent protection on R&D and patenting. Early contributions have found little impact of patent protection on innovation of domestic firms. These include Sakakibara and Branstetter (2001), who exploit a reform that increased patent scope in Japan, Lerner (2009) and Qian (2007) who analyse cross-country variation in patent protection over time. As argued by Bryan and Williams (2021), the lack of significant effects estimated in these studies could stem from small countries introducing relatively small changes that had little impact on global firms and large countries whose reforms could affect both domestic and foreign firms' innovation activities.

Evidence that patent protection is associated with higher innovative effort mostly comes from industry-specific case studies including cancer clinical trials (Budish et al., 2015) and plant biotechnology (Moscona, 2021). A notable exception is Arque-Castells (2022) who studies the establishment of the U.S. Court of Appeals which shifted the law enforcement in favour of patent holders. Arque-Castells (2022) finds that firms in industries with higher importance of patents experienced a relative increase in R&D expenditures following the introduction of the court.[3] We employ a related identification strategy which exploits cross-industry variation in the

[3]A related strand of literature studies how patents affect follow-on innovation (e.g., Galasso and Schankerman, 2015; Sampat and Williams, 2019) and has produced mixed results.

importance of patents.

Previous studies of price effects of patent protection have analysed the impact of patent expiration on drug prices (see Vondeling et al., 2018, for an overview) and consumer products in online markets (de Rassenfosse and Zhou, 2020). Duggan et al. (2016) study the effects of the TRIPS-compliant patent regime for pharmaceuticals in India and observe relatively modest increases in the price of a molecule following its patent approval. We contribute to this body of literature by recognizing that changes in prices only represent part of the equation regarding how stronger patents affect markups. Our findings suggest that firms benefit from cost-reducing innovations that are not accompanied by similar reductions in consumer prices.

The existing literature on the TRIPS-compliant patent reform in India has largely focused on studying the effects of the reform in the pharmaceutical sector (Kyle et al., 2023; Duggan et al., 2016; Chaudhuri et al., 2006; Chadha, 2009). This paper contributes to this literature by extending the analysis to all manufacturing industries in India. Moreover, we also analyse the effects of the reform on R&D, types of patents, markups and marginal costs. This broader set of outcomes allows us to obtain a more comprehensive understanding of how patent-induced innovation affects marginal costs and consequently markups.[4]

Our paper is also related to a growing literature on the evolution and determinants of market power (De Loecker and Eeckhout, 2018; Berry et al., 2019; Syverson, 2019; De Loecker et al., 2020). Recent studies emphasize the potential role of technology in shaping trends in markups within specific markets. These include Miller et al. (2024) for the cement industry, Grieco et al. (2023) for the automobile industry, Döpper et al. (2022) and Atalay et al. (2023) for consumer packaged goods, and Ganapati (2024) for wholesale trade. These papers indicate that markups have

[4]Bhattacharya et al. (2022) study a large set of industries and find that post reform, the share of managerial compensation increased more in firms with high technological intensity. Unlike this paper, our focus lies on examining the impact on innovation and market power, leveraging variation in exposure to the reform across industries.

mainly changed due to declining costs or increased quality.[5] We complement this literature by analysing the role of changing technology, induced by a patent reform, in affecting markups over time across a large range of manufacturing industries.

The rest of the paper is structured as follows. Section 2 discusses the institutional background and India's patent reform. Section 3 describes the data and measurement of our key variables. Section 4 presents the empirical strategy. The main results concerning the effects on innovation and market power, and the potential underlying mechanisms, are discussed in Section 5. Extensions and robustness checks are addressed in Section 6, Section 7 concludes.

2 The TRIPS compliant reform

Prior to joining the World Trade Organisation (WTO) in 1995, India had a weak patent law governed by the Patent Act, 1970.[6] In addition to a rather short patent protection duration of fourteen years, there were 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 only valid for a span of five to seven years and were subject to a system of licenses of right which effectively reduced the period of market exclusivity for patentees to three years (McLeland and O'Toole, 1987).

During the Uruguay round of General Agreement on Tariffs and Trade (GATT) negotiations, the US proposed to link Intellectual Property Rights (IPR) to trade through TRIPS. While developing countries, including India, initially showed resistance, they buckled under pressure of trade sanctions (EPW, 1989). Moreover, India ran into a balance-of-payment crisis by 1991, and the International Monetary Fund (IMF) conditioned its assistance on India opening its economy and becoming a member of the WTO. India signed the Marrakesh Agreement in 1994 to become

[5] De Ridder (2024) calibrates a quantitative model to show that changes in intangibles can explain markup trends in the French economy.

[6] The 1970 Act repealed the British era Patents and Designs Act, 1911.

part of the WTO and consequently agreed to introduce IPR reforms to comply with TRIPS over a ten-year period (1995-2005).

An immediate obligation under TRIPS was to introduce a "mailbox" facility starting from 1995 until December 31, 2004 to receive product patent applications in the field of pharmaceuticals, drugs and agrochemicals (Chadha, 2009). During the transitional period from 1995 to 2005, "mailbox patents" were provided exclusive marketing rights (EMRs) in cases where a patent was granted for the same product in another WTO member country after 1995 (Ram, 2005). To comply with this obligation, the government introduced The Patents (Amendment) Bill, 1995, but the bill was not passed due to strong opposition in parliament. This unsuccessful attempt to change the patent law was followed by several years of uncertainty. Even though the US and the European Commission filed complaints at the Dispute Settlement Body of the WTO against India for not abiding by TRIPS, no effective changes were made to the patent law between 1995 and 1998.

A change in government in 1998 paved the path for the first set of reforms. The Bharatiya Janata Party, which had been against the patent law, came to power in March 1998. The newly elected Prime Minister, who led a walkout from the parliament over the 1995 Amendment, conducted a nuclear test soon after assuming office. This controversial test strained relations with the West, resulting in sanctions.[7] To avoid further foreign policy conflicts, the newly formed government, contrary to its prior stand, agreed to proceed with the patent reform. The largest party in opposition, Congress party, too did not resist since it had previously signed the TRIPS agreement in 1995 (Reddy and Chandrashekaran, 2017, page 60). Thus, after a prolonged period of uncertainty, The Patents (Amendment) Act 1999 was passed in parliament, and came into effect from 26th March 1999. Thus, we define financial year 2000 as the first year of patent reform for pharmaceuticals and chemicals.[8]

[7] US imposed sanctions on India, CNN, 13 May 1998 http://edition.cnn.com/WORLD/asiapcf/9805/13/india.us/

[8] The financial year in India begins on April 1st and concludes on March 31st of the subsequent year. For example, financial year 1995 refers to the period from 1st of April 1994 to 31st of March 1995. Our data source, CMIE Prowess, also reports annual values based on the financial year.

While the legal reform for granting product patents in these industries happened in later years, innovation incentives and market power may have already responded to the initial changes in financial year 2000.

The second set of reforms were deliberated over by a joint parliamentary committee in the following years. Under TRIPS, many decisions concerning the patent law were left to the discretion of each sovereign state, creating uncertainty regarding when the new patent law would come into effect and what changes it would introduce. The Patents (Second Amendment) Act, 2002 was introduced in parliament after three years of deliberation. The reforms were applicable to all industries and brought a number of significant changes (e.g., Chaudhuri, 2002; Ram, 2005). These include an increase in the length of patent protection from 14 to 20 years and a deletion of the royalty limit for licensing process patents. Further, the burden of proof for cases of process patent infringement was reversed and fell upon the alleged infringer after the reform. The amendment also included new definitions of the terms "new invention" and "inventive step" which allowed for methods and processes of manufacturing to be patented. Based on the timing of the second set of reforms, we define financial year 2003 as the first year of reform exposure for all industries except pharmaceuticals and chemicals.[9]

The description of the institutional setting shows that there was widespread uncertainty in the initiation of the reforms, and adoption of these reforms is akin to a quasi-natural experiment.

3 Data and variables

3.1 Firm- and product-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 all publicly listed

[9]We check the robustness of our results to using a non-staggered timing of the reform where-in we define 2000 as the first year of reform for all industries.

companies in India and a large sample of private limited companies for which audited Annual Reports are available.[10] It is the largest and most comprehensive database on the performance of Indian business entities with the sample accounting for more than 70% of the industrial output of the organized sector and 71% of corporate taxes and 95% of excise taxes collected by the government (see, eg. Topalova and Khandelwal, 2011). The database contains high-quality information from company balance sheets and profit and loss accounts across all sectors since 1989. Thus, it reports several firm-level characteristics including, among others, revenues, tangible and intangible assets, investments, R&D, material and employment costs, financing conditions, ownership, and industry affiliation.

A unique notable feature of this dataset is that it records details of the product mix sold by firms in the manufacturing sector, including information on quantities and values of sales.[11] Indian firms are required by the 1956 Companies Act to disclose product-level information in their annual reports. The classification of products is largely based on the Indian National Industrial Classification (NIC) and the Harmonized Commodity Description and Coding System (HS) schedule. The product categories are disaggregated within industry groups, for example product categories include bread, shrimps, corned meat, pig iron, sponge iron, pipe fittings, rail coaches. However, they do not represent detailed varieties or brands of products.[12] Access to such product level information is important for our analysis since, as detailed below, it not only enables us to identify within-firm product changes in prices, but also facilitates markup and marginal cost estimation, and allows us to capture variation at firm-level in exposure to the patent reform (see section 3.3).

Prowess provides the registered name and address of the headquarters of a firm

[10] Availability of information through audited profit and loss statements, and balance sheets is the most important criteria for inclusion of companies in Prowess, and results in a sample primarily composed of firms accounting for significant economic activity.

[11] Another high-quality product-level data set for India is the Annual Survey of Industries (ASI). Unfortunately, a consistent product classification in the ASI data is only available from the financial year 2001 onwards which does not allow us to analyse pre-reform data. Further, the ASI data does not include firm names which are important to match patents as we discuss below.

[12] See Goldberg et al. (2010) and De Loecker et al. (2016) for a detailed description of the data.

which enables us to cross-reference patent applications filed by Indian firms at the Indian Patent Office with Prowess data.[13] Given that exact name matches across the two datasets is not always feasible, we employ fuzzy matching techniques. Details on name matching are outlined in Appendix C. We further assign a patent to a financial year using the priority or application date of the patent, whichever is earlier. This approach ensures that patents with a pre-reform priority date but a post-reform application date are not attributed as post-reform output.

3.2 Main outcome variables

To study the effect of the reform on patenting, first we calculate the number of patent applications filed by a firm in a given year. To examine the impact on actual innovative input, we use information on research and development (R&D) directly sourced from the financial accounts of firms in CMIE Prowess. While changes in patenting post reform could be driven by an increased incentive to protect innovation output, an effect on R&D expenditure would suggest that the reform also created incentives for investment in innovation.

To study the effect of stronger patent protection on market power, we estimate markups, and marginal costs following the methodology introduced by De Loecker et al. (2016). This method structurally estimates production functions for a firm i producing product p at time t:

$$Q_{ipt} = F_k(M_{ipt}, K_{ipt}, L_{ipt})\Omega_{it}$$

where Q_{ipt} denotes physical output, M_{ipt} denotes a freely adjustable input (materials in our case), K_{ipt} and L_{ipt} are capital stock and labor input, respectively and Ω_{it} denotes total factor productivity. A firm minimizes costs product-by-product subject to the production function $F(.)$, which is specific to sector k, and input costs. As shown by De Loecker and Warzynski (2012), this cost minimization yields

[13] We downloaded this data from the website of the Indian Patent Office, `https://ipindiaservices.gov.in/publicsearch`, between December 9, 2019 and January 6, 2020.

an expression for firm-product specific markup as:

$$\mu_{ipt} = \left(\frac{P_{ipt}Q_{ipt}}{W^M_{ipt}M_{ipt}}\right)\frac{\partial Q_{ipt}(.)}{\partial M_{ipt}}\frac{M_{ipt}}{Q_{ipt}} = \frac{\theta^M_{ipt}}{\alpha^M_{ipt}}$$

where P_{ipt} denotes the output price, W^M_{ipt} is the input price of materials, α^M_{ipt} is the ratio of expenditures on input M_{ipt} to a product's revenue and θ^M_{ipt} is the elasticity of output with respect to this input. θ^M_{ipt} can be estimated from a production function and α^M_{ipt} can be calculated once the allocation of inputs across a firms' product has been estimated. Marginal costs (mc_{ipt}) can then be recovered as the ratio of observed prices to estimated markups: $mc_{ijt} = P_{ijt}/\mu_{ijt}$

To estimate markups, we use a sector-specific translog production function which relates physical quantities to material, labour and capital inputs following De Loecker et al. (2016). The estimation routine recovers an estimate of markups and marginal costs for each product sold by a firm in a year. Appendix D provides further details of the estimation procedure.[14]

In the empirical analysis, we distinguish between products, industries, and sectors. Our measures of markups, prices and marginal costs vary at the (12-digit) product-level. Reform exposure varies at the (4-digit) industry level. We estimate production functions separately by (mostly 2-digit) sectors. For example, product categories such as "cycle tyres", "moped tyres", "foam & rubber mattresses" and "rubber foam" are mapped into industries "manufacture of rubber tyres and tubes" and "manufacture of other rubber products". These industries are a subset of the sector "Manufacture of Rubber and Plastic Products" (see Table A21 for the definition of sectors.)

To estimate the impact of the patent reform which occurred in early 2000s, we use data from CMIE Prowess from financial years 1995 to 2011. This time-frame allows us to capture years both prior to and long after the reform. We focus on firms and

[14]De Loecker et al. (2016) also use Prowess data to estimate markups, and provide details on the estimation procedure. We check the robustness of our results to accounting for firm R&D investment and patent applications filed in the productivity markov process.

Table 1: Summary statistics: Prowess data

Panel A: Firm-level data		
	Pre reform mean	Post reform mean
Patent applications	0.02	0.45
Is Patent applicant	0.01	0.05
R&D expenditure	3.49	13.09
Does R&D	0.26	0.32
Observations	20381	20616

Panel B: Product-level data		
	Pre reform mean (median)	Post reform mean (median)
Markup	6.43 (1.39)	6.36 (1.41)
Observations	37809	37671

Note: The table provides the mean and median (in brackets) before and after the patent reform. R&D expenditure values are measured in Rs. Million and deflated using the annual Consumer Price Index for India.

firm-products that were operational before the initiation of the TRIPS reform, that is from 1995 to 1999. This approach ensures that our findings reflect changes within firms and products and are not affected by firm entry or the introduction of high-markup products post-reform. Finally, since R&D and patents are only observed at the firm-year level, while markups, prices, and marginal costs are available at the firm-product-year level, we maintain comparability by restricting the sample to manufacturing firms for which we have product-level information.

Table 1 shows the summary statistics of our main outcome variables pre and post reform. As described in section 2, the reform kicked in earlier for pharmaceuticals and chemicals. Thus, we define the timing of the reform for a firm based on its' largest sales-weighted product group prior to the reform.[15] Panel (A) shows summary statistics of firm-level outcome variables, patent applications and R&D expenditure. Comparing the pre-reform and post-reform value shows that the average values of R&D expenditure, number of patent applications, and the likelihood of firms filing patents increased manifold post-reform. The increase in the likelihood

[15] In the baseline, we use data for all years for all firms. However, since pharmaceuticals and chemical industries are exposed to both the 2000 and 2003 reform, we check the robustness of our results to dropping observations for these firms post 2003.

of investing in R&D does not change importantly post reform.

Panel (B) of Table 1 shows the summary statistics of estimated firm-product level markups in our data. In this sample, while the mean markup is rather high, this is driven by a few products with extremely high markups.[16] The median markup of 1.4 is similar to previous research on Indian firms (e.g., De Loecker et al., 2016). The table shows that on average, there is no substantial change in firm-product markups post-reform. We document changes in the distribution of product-level outcome variables over time in Figure A1.

3.3 Exposure to reform

Industry surveys show 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 (at least from 2003 onwards) potentially affected innovation incentives in all industries, we exploit variation in the reliance on patents as a mechanism of appropriation across industries. In the baseline, we borrow a measure of patent intensity at four-digit industry level from EPO (2013). The main assumption we make behind using patent intensity from EPO to measure exposure to the patent reform in India is that reliance on patenting as an appropriating mechanism is an intrinsic character of an industry, irrespective of location and time.[17] Using European data also ensures that the importance of patenting as an appropriation mechanism is driven primarily by technological factors, rather than being influenced by constraints such as limited financing, or inadequate judicial services within India.

EPO (2013) is a joint statistical effort made by the European Patent Office (EPO) and the Office for Harmonization in the Internal Market (OHIM). They match patent data from the database PATSTAT (developed by the EPO and the OECD) with

[16]Our estimation results are robust towards different outlier corrections.

[17]Different data checks support this assumption. First, we find that there is high correlation between industry-level measures of patent intensity from EPO (2013) and EPO (2019) which use data from 2004-2008 and 2010-2014 respectively. Second, we show that using data from US to measure patent intensity is highly correlated with the measure from EPO (2013).

the commercial database ORBIS (provided by Bureau van Dijk). ORBIS contains industry classifications 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 firms in each four-digit NACE industry divided by total employment for that industry, leading to an indicator of patent numbers per 1,000 employees. We merge the patent intensity measure defined for four-digit NACE industries with firm-products in Prowess. First, we define a four-digit NIC (National Industrial Classification of India) industry code for each 12-digit product code reported in Prowess. Then, we use a concordance between NACE four-digit and NIC four-digit to merge the EPO-OHIM patent intensity measure with Prowess data. Thus, for each product of a firm, we obtain an estimate of exposure to the reform.[18] Table A3 shows the summary statistics. The average value of patent intensity for our firm-product level panel is 3.27, with a standard deviation of 4.04.

To estimate exposure to the reform at the firm-level, we calculate a sales-weighted measure of patent intensity using the product-mix manufactured by a firm prior to the initiation of the reform in 2000 as follows:

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

where i is the firm, j is the four-digit industry to which 12-digit products of a firm are mapped, and t is the financial year. Out of 4182 firms, 1866 firms in our sample produce more than one product, and 1092 operate in more than one four-digit industry. Thus, using a sales-weighted measure of patent intensity to capture firm-level exposure to the reform allows us to exploit greater variation. Following equation (1), the average value of patent intensity for our firm-level panel is 2.95,

[18]The report shows the value of patent intensity for industries with above average patent intensity. For all the other industries that have a below average measure of patent intensity, we impute the lower bound (0.697 patents per 1000 employees). We check the robustness of our result to (a) using zero as the value of patent intensity for industries with below average patent intensity, and (b) to using a binary variable for above average exposure to the reform instead of a continuous measure.

with a standard deviation of 3.78.

Although our measure of exposure to the reform is based on the assumption that patent intensity across industries is time and location invariant, it could be that the patent reform in India was staged to happen such that the reform would provide a boost to firms and industries already growing prior to the reform. A particular concern is that exposure to the patent reform is correlated with trade exposure and market access due to India's trade liberalization (which mainly happened during the 1990s) and WTO membership. In Table A1, we therefore study the correlation of patent intensity across industries with changes in output and input tariffs as well as export and import growth during the pre-patent-reform period. In Table A2, we study the correlation of firm-level patent intensity as calculated in equation (1) with pre-reform indicators of firm growth and R&D expenditures. We find that patent intensity at industry and firm level is not statistically significantly correlated with pre-reform industry and firm performance. The estimated coefficients also indicate quantitatively small correlations. For instance, moving from the lowest value to the mean value of patent intensity is associated with less than 1.2% higher output growth and less than a 1.2% reduction in output tariffs over a 4-year period.

As an alternative measure of patent intensity at industry level, we combine patent filings at the USPTO from 1990 to 1999 with firm-level data from Compustat. We describe the construction of this measure in Appendix B and document its correlation with the the baseline measure of patent intensity in Figure A2 . Given that Compustat data is only available for publicly listed firms in the United States, we prefer using the measure from EPO (2013) for our baseline specification.

4 Empirical Strategy

Firm-level specification

We evaluate the impact of the patent reform on R&D and patenting measured at the firm-level as follows:

$$E[y_{it}] = G(\beta Post_{kt} \times PatentIntensity_i + \lambda_{kt} + \lambda_i + [x'_{i(j)t}\gamma]) \quad (2)$$

where y_{it} is the outcome of a firm i in year t. We use several alternative functional forms and transformations of the dependent variable. To approximate relative changes in our variables of interest, we use the inverse hyperbolic sine transformation of both the number of patent applications and R&D expenditure. We analyse changes on the extensive margin by using a patent application dummy, and a dummy for firms incurring R&D expenses. Finally, we use the raw values of the number of patent applications and R&D expenditure and estimate a linear specification by OLS and an exponential specification by poisson quasi maximum likelihood.

$Post_{kt}$ is a sector-specify dummy equal to one from financial year 2000 onwards for firms whose largest share of sales prior to financial year 2000 is from pharmaceuticals or chemicals, and equal to one for all other firms from financial year 2003 onwards. $PatentIntensity_i$ denotes time-invariant firm-level exposure to the reform as defined by equation (1). Firm fixed effects (λ_i) absorb time-invariant differences between firms, and sector-year fixed effects (λ_{kt}) account for sector-level shocks and subsume the direct effect of $Post_{kt}$. We use ten broad mostly two-digit sectors for the sector-year fixed effects where a firm's sector is the one with the highest sales share prior to the reform. We use sector-year (not industry-year) fixed effects because over 50% firms in our sample are single-product firms, and hence a large share of variation in $PatentIntensity_i$ is at the four-digit industry level. We add firm- and industry-level controls ($x_{i(j)t}$) in section 6.

Our coefficient of interest is β which estimates the relative change in innovative activity or patenting post-reform when patent intensity takes on a value of one. We cluster standard errors at the firm level.[19]

[19] The significance of results is not affected by clustering the standard errors at four-digit industry level.

Recent research points to potential bias in difference-in-differences specifications with varying treatment timing that results from earlier treated units acting as control observations for later treated units (e.g., Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2023; Callaway and Sant'Anna, 2021; Borusyak et al., 2024). Since our measure of exposure to the reform is non-binary, the standard remedies in the staggered difference-in-differences literature are not applicable. We check the robustness of our estimates towards setting a common first date of treatment exposure for all industries. This alleviates concerns that the estimated effects are affected by bias from heterogeneous treatment effects across treatment cohorts and time.

We also conduct an event study by estimating the following regression which allows the effect of reform exposure to vary over time[20]:

$$E(y_{it}) = G(\sum_{\tau=-5}^{8} \beta_\tau Post_{k\tau} \times PatentIntensity_i + \lambda_{kt} + \lambda_i + [x'_{i(j)t}\gamma]) \qquad (3)$$

Since the patent reform kicked in earlier for pharmaceuticals and chemicals, we define financial year 2000 as $\tau = 0$ for these sectors. For all other sectors, we define financial year 2003 as $\tau = 0$. We estimate separate coefficients for each of the 5 years before and 8 years after the policy change, while leaving the rest of the specification unchanged. We normalize the coefficient β_{-1} to zero. The coefficients of $\beta_{-5}, ..., \beta_{-2}$ serve as a placebo test on whether firms may have anticipated changes in patent protection or more generally whether pre-reform trends vary across firms and industries with different exposure to the reform.

Firm-product-level specification

We estimate the effect of the reform on firm-product level outcomes using the fol-

[20]Event studies also address bias from time-heterogeneous treatment effects as long as their pattern is similar across treatment cohorts (e.g., Goodman-Bacon, 2021; Sun and Abraham, 2021).

lowing equation:

$$\ln(y_{ip(j)t}) = \beta Post_{kt} \times PatentIntensity_j + \lambda_{kt} + \lambda_{ip} + [x'_{ip(j)t}\gamma] + \epsilon_{ipt} \qquad (4)$$

where $\ln(y_{ip(j)t})$ is the log of markup, marginal cost, or price of a 12-digit product p, which is mapped to a four-digit industry j in sector k, that is produced by firm i during year t.[21] $Post_{kt}$ is a dummy equal to one from financial year 2000 onwards for all products mapping into two-digit sector k for pharmaceuticals and chemicals, and it is equal to one for the rest of the products from 2003 onwards. $PatentIntensity_j$ is a time-invariant four-digit industry-level measure of the exposure to reform borrowed from EPO (2013). We include firm by 12-digit product fixed effects (λ_{ip}) to control for time-invariant differences between firm-product combinations. Sector-year fixed effects (λ_{kt}), which subsume the direct effect of $Post_{kt}$, control for time varying sector level shocks and ensure that the identification comes from comparing firm-products within a sector. We add time-varying firm- and industry-level controls ($x_{ip(j)t}$) in robustness checks discussed in section 6.

Our coefficient of interest is β which estimates the relative (approximately percent) change in $y_{ip(j)t}$ after the reform, e.g. for a product with a patent intensity index of one relative to a product with a patent intensity index of zero. Since markups and marginal costs are estimated from the production function, we bootstrap the standard errors with clustering at four-digit NIC industry level. We use wild cluster bootstrap since our 102 four-digit NIC industry groups are heterogeneous in size.

Analogous to equation (3), we also estimate an event-study specification for product-level outcomes:

$$\ln(y_{ip(j)t}) = \sum_{\tau=-5}^{8} \beta_\tau Post_{k\tau} \times PatentIntensity_j + \lambda_{kt} + \lambda_{ip} + [x'_{ip(j)t}\gamma] + \epsilon_{ipt} \qquad (5)$$

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

Table 2: Effect on patenting and R&D

Dependent Variables:	Patent applications	Is Patent applicant	R&D expenditure	Does R&D
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0207***	0.0084***	0.0366***	0.0021
	(0.0041)	(0.0015)	(0.0087)	(0.0021)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	40,997	40,997	40,997	40,997
R^2	0.55550	0.42351	0.81286	0.75529

Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in a given year. The independent variable *Post* equals one from 2000 onwards for firms whose largest share of sales pre 1999 is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. $PatentIntensity$ denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

5 Empirical Results

5.1 Effect on patenting and R&D

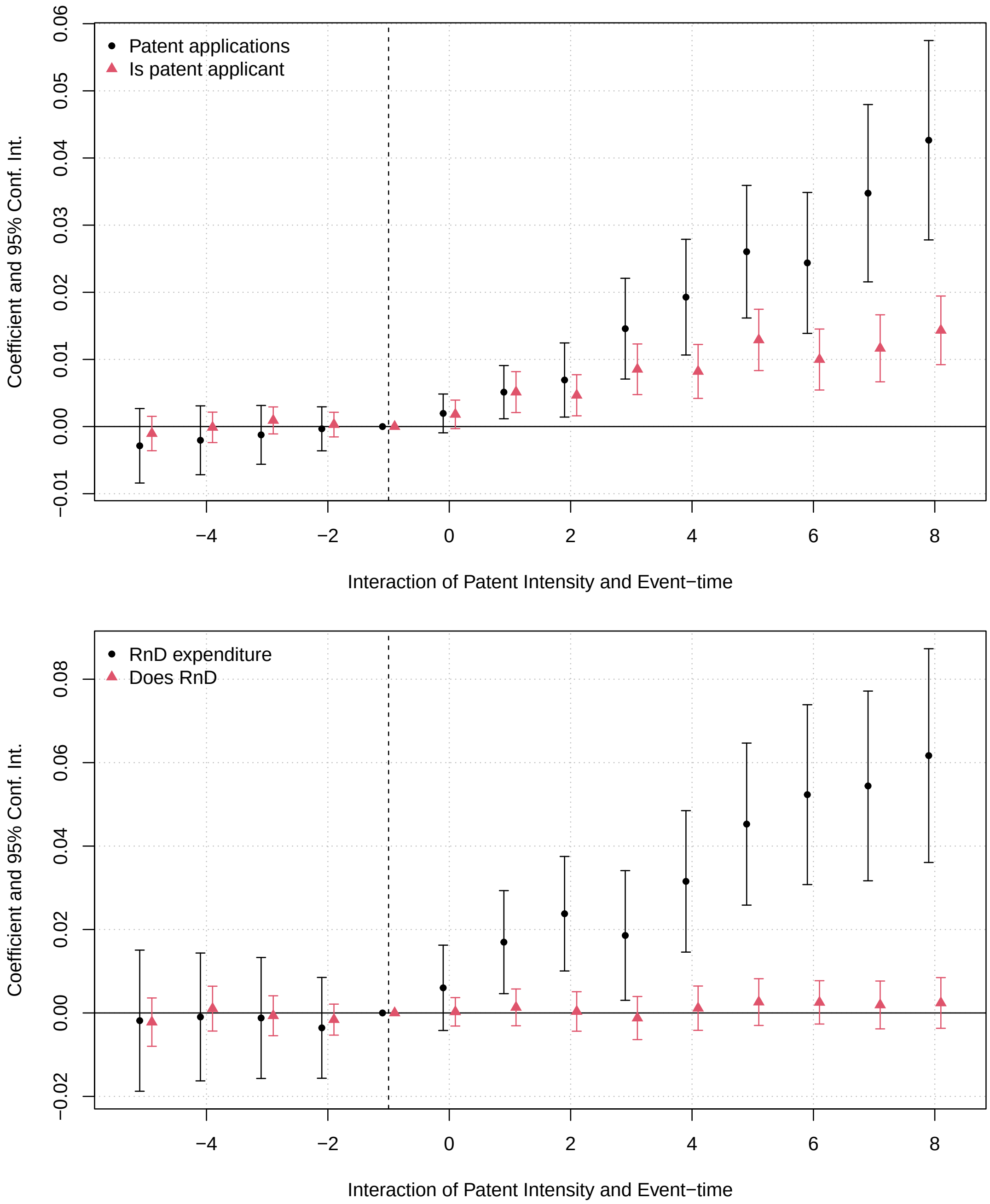
Following equation (2), Table 2 shows the baseline result for R&D and patenting. These are based on an inverse hyperbolic sine transformation of the dependent variable and a dummy variable indicating positive values. Table A4 shows results using outcome variables in levels and estimating a linear and alternatively an exponential specification. Columns (1) of Table 2 shows that the coefficient of interest, $Post \times PatentIntensity$, is positive and statistically significant for the number of patent applications filed at the Indian Patent Office. In terms of the economic magnitude, the estimates indicate that relative to firms active in product-markets with the lowest patent intensity (0.697), firms in product-markets with mean patent intensity (2.95) increase patenting by approximately 4.6%. Column (2) shows that the reform has a positive and significant effect on the extensive margin of patenting as well. Thus, along with an increase in the number of patents filed by a firm, there is an increase in the number of firms that patent in a given year post reform.

Patenting can, obviously, increase after the reform because of higher incentives to innovate and/or because of higher incentives to patent a given innovation. We therefore turn to results on innovation input, measured by R&D, next. Column (3) shows that the estimated effect of the reform is indeed also positive and statistically significant for the level of R&D expenditure. The estimates indicate that relative to firms active in product-markets with the lowest patent intensity, firms in product-markets with mean patent intensity increase R&D expenses by approximately 8.2%. Thus, the relative effect for R&D expenses is even somewhat larger than the relative increase in patenting. The estimated effect on the extensive margin of R&D expenses in Column (4) is positive, but not statistically significant. Thus, the probability to engage in R&D increases to a lesser extent than the likelihood of patenting. To summarise, baseline results suggest that firms most exposed to stronger patent protection, i.e. firms selling products that rely heavily on patents as an appropriation mechanism, not only filed more patent applications to the Indian Patent Office, but also had higher incentives to invest in innovation activities after the patent reform.

In Table A4 we show that our conclusions are qualitatively similar when we use R&D expenditure and patent applications in levels as the dependent variable and use OLS (columns 1 and 2) or an exponential mean specification, estimated by poisson quasi maximum likelihood (columns 3 and 4).

Next, we study the dynamic effects of the reform by conducting an event study following equation (3). Figure 1 plots the coefficients and 95% confidence intervals for each event year interacted with $PatentIntensity_i$. The graph indicates that prior to the reform the *growth* rates of patent applications and R&D expenditures, as well as changes to the extensive margin, were not statistically significantly different for firms more exposed to the reform. Thus, as argued in section 2, firms did not seem to have anticipated how and when the patent reform was going to be implemented

Figure 1: Patents and R&D: Dynamic effect



Notes: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in a given year. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Event-time 0 refers to year 2000 for firms whose largest share of sales pre 1999 is from pharmaceuticals or chemicals, and year 2003 for all other firms. Standard errors are clustered at firm level.

after India became part of WTO in 1995.[22] The presence of small and insignificant pre-reform coefficients supports the assumption that our patent intensity measure is not picking up differential trends across firms and industries, or the effects of previous policy changes. It also alleviates concerns that the reform was introduced to favour firms that were already increasing their innovation activities before its implementation.

Examining the effect from event time 0 onwards, Figure 1 shows a positive and statistically significant change in R&D and patenting of firms most exposed to the reform as early as one year after reform implementation. Both outcomes gradually increase over time, and the effect persists for at least eight years after the reform. We do not observe an abrupt, short-lived increase in patenting immediately following the reform due to firms patenting their existing innovations. Instead, we notice a gradual rise, which suggests that the reform represented a persistent change in patenting incentives, not just a one-time shift. The gradual effect on R&D expenditure further corroborates the finding that the reform changed the incentives to spend on innovation. The estimated coefficients suggest that, relative to firms active in product markets with the lowest patent intensity, firms in product markets with average patent intensity increased patenting by about 9.6% and R&D expenditure by around 13.9% towards the end of our sample period, respectively. These increases correspond to an average increase in growth rates of about 1.2% and 1.7% per year after the reform. Looking at the extensive margin, the reform appeared to incentivise many more firms to start patenting, however, it did not provide sufficient incentive for firms to initiate investments in R&D activities.

In addition to the quantity of patent applications, we use several proxies of patent quality to study if the reform also led to allocation of resources towards high-impact, high-value innovation.[23] Results are reported in Table 3. We find that the reform

[22]For the sub-sample of sectors that were only affected by the second set of reforms in financial year 2003, we also do not find any pre-trends between 2000 and 2003. This result is consistent with widespread uncertainty regarding the passing of the 2003 reforms and no change in innovative effort in anticipation.

[23]Unfortunately, our data does not contain information on citations which are often employed

Table 3: Effect on patent quality

Dependent Variables:	Granted patents	Avg. no. of inventors	No. of patents renewed	Patents abroad	Family size
Model:	(1)	(2)	(3)	(4)	(5)
Post * Patent Intensity	0.0087***	0.0277***	0.0074***	0.0141***	0.0259***
	(0.0024)	(0.0050)	(0.0022)	(0.0033)	(0.0061)
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes	Yes
Observations	40,997	40,997	40,997	40,997	40,997
R^2	0.51823	0.44554	0.51195	0.59427	0.36845

Note: The dependent variable *Granted patents* is the inverse hyperbolic sine of the number of patents filed by a firm in a given year that are granted at a later date. Avg. no. of inventors is the average number of inventors listed on patents filed by a firm in a given year. Number of patents renewed is the number of patents filed by a firm in a given year that are renewed later. Patents abroad is the inverse hyperbolic sine of patents filed outside India by a firm in a given year. Family size is the average DOCDB simple family size of a patent filed outside India. The data for Columns (4) and (5) is taken from PATSTAT Global Spring 2023 edition. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

is associated with an increase in the number of granted patents in Column (1). Additionally, there is a positive effect on the average number of inventors per patent in Column (2). The number of inventors per patent can be interpreted as a quality-weighted measure as larger teams are usually associated with higher impact and a larger number of citations, but they also entail larger costs (Wuchty et al., 2007). Column (3) shows a positive effect on the number of patents that are renewed, reflecting the private value of the patents to a firm (Lanjouw et al., 1998; Bessen, 2008).

Further, we examine the number of patents filed abroad. Filing abroad is an additional expense and firms would opt for a broader geographical protection only if they

as a quality-adjusted measure of patent counts in the literature.

consider the invention to be valuable enough. To measure patent filings abroad, we match firm-level CMIE Prowess data with patent data from PATSTAT. Our results indicate that patent filings abroad increased with reform exposure (Column 4). The coefficient is smaller than the coefficient for number of patents filed in India (Table 2, Column 1) suggesting that firms filed fewer, possibly only the most valuable patents, internationally. Additionally, the average family size of foreign patents per firm also increased post-reform (Column 5), suggesting that firms considered some of their patents valuable enough that they were willing to invest in patent protection across jurisdictions. In sum, the reform seems to have stimulated the creation of high-quality patents.

5.2 Effect on markups, prices, and marginal costs

A major concern of stronger patent protection is that it allows inventors to charge a higher markup. 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 for each product sold by a firm in a given year. Following equation (4) to estimate the effect of the patent reform on firm-product-level outcomes, Table 4 shows the results. Since we compute standard errors from wild cluster bootstrap, the table shows confidence intervals and the level of significance of our key coefficient, $Post \times PatentIntensity$.

In column (1), the coefficient on $Post \times PatentIntensity$ is positive and statistically significant, suggesting that post reform, the average markup within firm-product groups most exposed to the reform increased. The estimates indicate that relative to product-groups with the lowest patent intensity, markups increased by 6.1% for products with mean patent intensity after the reform. By definition, markups can increase due to higher prices or lower marginal costs. Column (2) shows a small positive but statistically insignificant effect on prices, and Column (3) shows a negative and statistically significant effect on marginal costs. The estimates in Column (3) indicate that relative to product-groups with the lowest patent intensity, marginal

Table 4: Effect on Markups, Prices and Marginal Costs

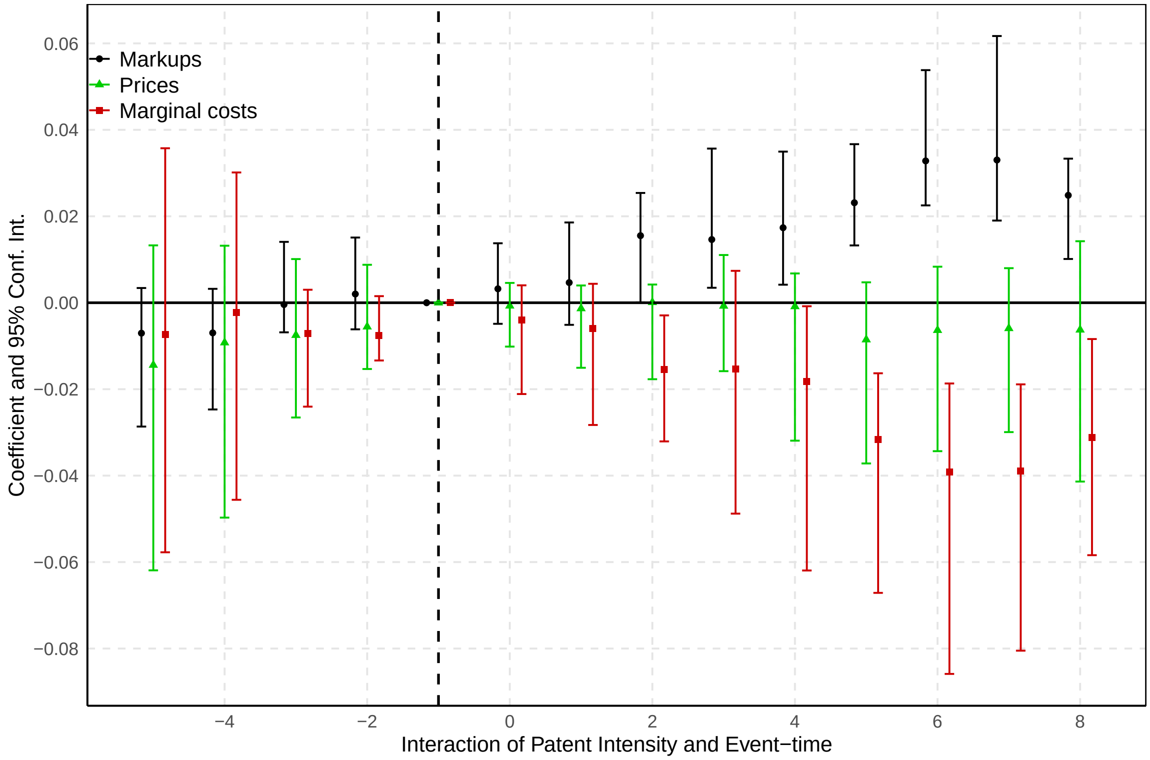
Dependent Variables:	Log markup	Log prices	Log marginal cost
Model:	(1)	(2)	(3)
Post * Patent Intensity	0.0236***	0.0039	-0.0197**
	[.01446, .03602]	[−.01682, .02567]	[−.0485, −.006779]
Fixed-effects			
Firm-Product-Unit	Yes	Yes	Yes
year_ind	Yes	Yes	Yes
Observations	75,480	75,480	75,480
R^2	0.77964	0.96971	0.93084

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%.

costs decreased after the reform by 5.1% for products with mean patent intensity. Altogether, the results show that the increase in markups after the implementation of the patent reform is explained largely by a decline in marginal costs, rather than an increase in prices.

Next, we study the dynamic effect of the reform on markups, marginal costs, and prices following equation (5). Figure 2 shows the coefficients and 95% confidence intervals for each of the three dependent variables. Prior to the onset of the reform, specifically from event time -5 to -2, we do not find any significant differences in the growth rates of markups, prices and costs by exposure to the reform. Thus corroborating previous evidence, the results are consistent with no anticipation of the details of the reform. Moreover, the lack of pre-trends indicates that our measure of patent intensity is not merely picking up trends in four-digit industries that might influence firm-product markups.

Figure 2: Markups, prices and marginal costs: Dynamic effects



Notes: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. $PatentIntensity$ is the four-digit NIC group level measure of patents per 1000 employees. Event-time 0 refers to financial year 2000 for pharmaceuticals and chemicals, and 2003 for all other industries. Wild cluster bootstrap confidence intervals are shown as errorbars. Clustering is at NIC four-digit level.

Examining the coefficients from event time 0 onwards shows that the reform had a positive and statistically significant effect on markups a few years after the initiation of the reform. The increase in markups is gradual and persistent, in line with the gradual increase in innovative activities of firms post reform. The increase in markups is due to a decline in marginal costs, also observed a few years after the reform. We do not find significant changes in prices in any of the post-reform periods. The existence of a lag between filing a patent and converting it into a usable technology offers a plausible explanation for the delayed effect of the reform on marginal costs and markups.

To make the results on prices, markups, and marginal costs directly comparable to the firm-level results on patenting and R&D, we create indices of these variables at the firm-level.[24] Figure A3 shows the dynamic effects of the reform on markups, prices and marginal costs at the firm-level. The results are very similar to the results at product-level shown in Figure 2. This is reassuring given recent evidence that, compared to firm-product-level markups, firm-level markups are more robust towards within-firm productivity differences and different assumptions about joint production (Cairncross et al., 2023).

In support of the result of higher firm-level markups, Table A6 shows that the profitability of a firm more exposed to stronger patent protection increases post reform. We measure profitability by economic profits, defined as total sales minus labour, material, and capital costs. This indicates that the markup increases were large enough to outweigh any changes in fixed costs.

In the next subsection, we discuss potential mechanisms driving marginal cost reductions, followed by a discussion of the possible reasons for changes in markups.

5.3 Declining marginal costs, process innovations and scale economies

In this section, we discuss potential channels that could explain the fall in marginal costs after the patent reform.

First, the decline in marginal costs could be due to firms directing innovation effort towards improving or developing new processes that potentially help the firm save costs. Unfortunately, it is not possible to directly distinguish between R&D

[24]Following Smeets and Warzynski (2013), we calculate annual growth rates for each firm-product combination and compute a weighted growth rate at the firm level using the average sales value of that product. Missing growth rates are imputed initially at the four-digit NIC level, then at the two-digit NIC level, and finally at the year level. In 1994, all firms are assigned a value of 1, and the growth rate is used to calculate the index.

expenditures directed towards process and product innovations in our data. Hence, to study this channel, we categorise patents into process and product patents using keywords suggested by Banholzer et al. (2019). We identify keywords related to process and product patents in the abstract, claims and title of the patent as discussed in Appendix C, and use the relative share of process patent keywords versus product patent keywords to create three groups: (a) patent applications with largely process innovation related keywords, (b) those with largely product innovation related keywords, and (c) those that are mixed and include a similar proportion of both product and process innovation related keywords. We are able to classify roughly 90% of the patents matched to firm-level Prowess data into one of the three groups. Groups (a) and (b) account for an equal share, roughly 40%, of all the categorised patents, and the remaining 20% are categorised as mixed patents.

To estimate the impact of the reform on the type of patents, we use the number of process, product, and mixed patents by a firm in a given year as the dependent variable in equation (2). Results are reported in Table 5. We find that the reform had a positive and significant effect on all three types of patents, but the effect is 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). The estimates indicate that relative to firms active in product-markets with the lowest patent intensity (0.697), firms in product-markets with mean patent intensity (2.95) increase patenting of new processes by approximately 3.2%, of new products by 2.3%, and of mixed patents by 2.1%.

Figure A4 shows the dynamic effect of the reform on different types of patents. Prior to the reform, the coefficients are small and statistically insignificant for all types of patents. After the reform, however, all types of patent applications gradually increased for firms more exposed to the reform. The effect persisted for several years post reform, and remained economically largest for the number of process patents. The large effect of the reform on process patents is not surprising. The

Table 5: Product versus process patents

Dependent Variables:	Process patents	Product patents	Mixed patents
Model:	(1)	(2)	(3)
Post * Patent Intensity	0.0144***	0.0105***	0.0094***
	(0.0032)	(0.0024)	(0.0023)
Fixed-effects			
Firm	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	40,997	40,997	40,997
R^2	0.51496	0.50371	0.50848

Note: The dependent variables *Process patents only*, *Product patents only* and *Product + Process patents* is the inverse hyperbolic sine of the number of the type of patent applications filed by a firm in a given year. The independent variable *Post* equals one from 2000 onwards for firms whose largest share of sales pre 1999 is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. Significance level: * 10%, ** 5%, *** 1%.

reform explicitly removed licensing obligations for process patents, extended the term of process patents for sectors which previously had these protections, and reversed the burden of proof in cases of process patent infringement now to the alleged infringer. These changes seem to have increased the incentives for firms to invest in process patents. In Appendix C.2, we provide several examples of patent applications that we classify as process patents where the title and/or the abstracts show how cost-reduction is an imperative part of such applications.

Additionally, the decline in marginal cost within product groups most exposed to the patent reform might be an outcome of higher output and a consequent reduction in cost of production at the margin due to scale economies. This mechanism is plausible given that granting patents is expected to significantly decrease instances of imitation within patent intensive product groups, thereby potentially redirecting demand towards patent holders. To study this second mechanism, we estimate the impact of the reform on quantities sold following equation (4).

Table 6 shows the result. Column (1) shows an increase in quantity sold on average *within firm-products* after the reform. In other words, there is a relative increase in the quantity sold of those products of a firm that have a high propensity to rely on patenting as an appropriation mechanism. Moreover, results in column (2)-(5) show that the increase in quantity sold and decline in marginal costs is concentrated in industries with scale economies.[25]

Comparing the average effect of the reform on quantity sold in column (1) of Table 6 with the average effect on marginal costs in Table 4 column (3), we observe that the relative increase in average output is of similar magnitude as the relative decline in marginal costs. Thus, while increasing output can explain some of the cost reductions, this is unlikely to be the main explanation.[26]

5.4 Potential mechanisms behind increasing markups

Results of subsection 5.2 indicate that, from a mechanical perspective, markup increases are due to declining costs rather than increasing prices, and the previous subsection indicates that these cost declines might be explained by incentives to invest in process innovations. In product-markets with imperfect competition, marginal cost declines do not lead to a one-to-one decline in prices. In line with De Loecker et al. (2016), we find that in our sample, a marginal cost reductions of 1% within firm-products is, on average, associated with an increase in markups of about 0.65% and reduction in prices of about 0.35%, consistent with incomplete pass-through. If marginal costs decline as a result of cost-reducing innovations induced by the reform, it is thus plausible that markups increase.

[25]We use the classification of scale economies as defined by Davies and Lyons (1996) for NACE three-digit industries. We map this classification to NIC three digit industries and use the average value to split firm-products into two groups.

[26]For instance, for the average estimated returns to scale parameter of 1.1 in our sample, a Cobb Douglas production function would imply that a 1% increase in output is associated with a 0.1% reduction in marginal costs. In a translog production function, cost reductions induced by a 1% output increase can be somewhat larger but are unlikely to exceed 0.2%-0.3% (see Stiebale and Vencappa, 2018).

Table 6: Output and marginal costs

Dependent Variables:	Log quantity sold			Log marginal cost	
Scale economies:		No	Yes	No	Yes
Model:	(1)	(2)	(3)	(4)	(5)
Post * Patent Intensity	0.0126**	-0.0315	0.0415***	0.0328	-0.0491**
	[.00360, .03811]	[-.09358, .04692]	[.01531, .0819]	[-.1329, .08723]	[-.08167, -.005921]
Fixed-effects					
Firm-Product-Unit	Yes	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes	Yes
Observations	75,480	37,888	37,011	37,888	37,011
R^2	0.94342	0.94042	0.94521	0.93095	0.93075

Note: The dependent variable *Log of quantity sold* is the log of output sold by a firm of a given 12 digit product-unit combination in a year. *Log marginal costs* is the difference of log of prices and log of markups estimated following De Loecker et al. (2016). The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC industries from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Columns (3) and (5) show the results for the sub-sample of three-digit industries classified as those with scale economies, and Columns (2) and (4) for the others. Wild cluster bootstrap confidence intervals are reported in brackets. Standard errors are clustered at four-digit NIC group level. Significance level: * 10%, ** 5%, *** 1%.

There are several alternative channels that could explain why markups increase in response to stronger patents. First, exclusive rights granted with a patent could increase market power and, ceteris paribus, lead to higher prices. Second, if firms increase the quality of their products, they are likely to face a lower elasticity of demand, allowing them to charge higher markups. The increase in product patents (which could reflect new or improved products, or a higher incentive to patent product innovations) and output expansions, documented in the previous subsection, are consistent with the second explanation. While both channels cannot explain why costs fall and prices do not increase significantly, they could explain increases in markups and prices *conditional* on marginal costs, in contrast to the incomplete pass-through channel.

We study the change in markups, controlling for log marginal costs, squared and cubic values, in Table A5. The coefficient for $Post \times PatentIntensity$ in column (1) is positive but less than half the size of the markup coefficient in Table 4 and is not statistically significant. In column (2), we repeat the exercise but instrument functions of marginal costs with their lagged value, and estimate very similar coefficients. Thus, a substantial part of the increase in estimated markups seems to be due to an incomplete pass-through of cost savings.

We also investigate the potential role of quality upgrading more directly. Assuming that higher quality products use more expensive inputs, we exploit information on the prices of each raw material used by a firm directly from CMIE Prowess. We relate material prices at the firm-input-year level to firm-specific reform exposure (as in equation (2)), controlling for firm-input fixed effects and sector-year fixed effects. Table A7 shows no significant change in material prices post reform. All in all, while we cannot rule out that quality upgrading and exclusive rights granted through patents explain some of the increase in markups, the effects of these channels seem to be rather small relative to the effects from cost reductions.[27]

6 Additional robustness tests and extensions

We conduct several additional robustness checks which we briefly describe here and in more detail in Appendix B. A first set of checks examines the sensitivity towards additional control variables. For this purpose, we control for various additional policy changes in India that could affect innovation and market power, including trade policy, FDI liberalization, delicensing and R&D tax credits. Results documented in Table A8 and A9 and Figure A5 confirm our conclusions. Furthermore, we account for firm characteristics that may be correlated with the exposure of firms to the reform. We control for differential trends for firms of different size, ownership, export and import intensity (Table A10, Table A11 and Figure A6). In alternative specifications, documented in Table A12 and A13, we control for unit-specific prereform trends estimated from observations before the first reform year as suggested by Goodman-Bacon (2021).

[27]An alternative proxy for product quality would be to measure demand conditional on price, for instance, based on the indicators proposed by Amiti and Khandelwal (2013) and Khandelwal et al. (2013). However, in our application, where market shares might change as a result of stronger patents, it is not clear how well variation in these measures captures changes in product quality.

A second set of robustness checks examines the sensitivity of our results towards different measure of reform exposure. First, we construct an alternative measure of patent intensity, based on patent filings of listed firms in the US before the Indian patent reform (Table A14 and A15 and Figure A7). Second, since the reform was initiated in financial year 2000, we define it as the first year of reform for all industries (see Figure A8).

A third set of robustness checks refers to the measurement of markups. The results are robust to removing outliers (see Table A16), and 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 by a Cobb-Douglas production function (see Table A17).

We study heterogeneity for firms of different size in Tables A18 and A19. Interestingly, the effects on process innovations, R&D investments, and marginal costs are concentrated among relatively large firms which is in line with the literature suggesting that large firms have a stronger incentive to invest in process innovation (Cohen and Klepper, 1996; Akcigit and Kerr, 2018). In Table A20, we report heterogeneous effects across product groups characterised by a higher concentration of sales, where concerns about increasing markups and prices might be most pronounced. The increase in markups is somewhat larger for products characterised by higher concentration of sales. However, for both groups the increase in markups does not seem to stem from higher prices.

Finally, we examine whether the reform had an impact on other types of investments besides R&D. For this purpose, we examine the dynamic effect of the reform on investment in capital goods, defined as the inverse hyperbolic sine of the change in gross fixed assets. The results are presented in Figure A9. There are some positive coefficients in post-reform periods, but there does not seem to be a gradual increase as the one we measure for innovation investment. In alignment with the intended focus of the patent reform, the effect appears to be concentrated on innovative activities rather than encompassing all types of investment. This result also indicates that our estimated effects on innovation, patenting and market power are unlikely to pick up differential investment patterns across industries.

7 Conclusion

This paper provides empirical evidence on the effect of stronger patent protection on innovation activities of firms and their ability to exert market power. It contributes to the long standing debate on the trade-off between dynamic and static efficiency effects of intellectual property rights.

We bring evidence from India, an important developing country, where the adoption of a TRIPS compliant patent reform in early 2000s 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 different industries rely on patents to protect their innovations. Along with using information on R&D expenses of firms, we match patents filed at the Indian Patent Office with our firm-level data to measure the effect of the reform on innovation and patenting of firms. Since our data provides information on the prices and quantities of products sold by a firm in any given year, we are able to capture variation in the exposure to the reform at firm-level using their pre-reform product mix. Moreover, the product-level data helps us estimate firm-product level markups using state of the art methods and to study the impact of the reform on market power and marginal costs.

We find robust evidence that stronger patent protection leads to an increase in patenting, quality-adjusted patents, and R&D expenses for firms producing products that rely importantly on patenting as an appropriation mechanism. We also estimate an increase in firm-product level markups after the reform. The rise in markups is primarily driven by a decline in marginal costs which are not passed on to the consumers in the form of lower prices. We identify two mechanisms explaining the decline in marginal costs due to the patent reform. Firstly, equipped with matched patched data, we find that the reform led to a significant increase in the number of process patents filed by firms. Secondly, we provide evidence for output expansion in industries with scale economies.

Overall, the results of this paper suggests that—at least in the case of India—stronger patent rights have fostered innovation with limited price effects for the average industry. However, due to increasing markups, the gains from patent protection have predominantly accrued to producers rather than consumers and buyers. The mechanism uncovered in this study underscores the significance of cost-saving innovations in shaping the technology driven rise in markups, thereby presenting important implications for policy-makers that aim to redistribute gains from technological growth.

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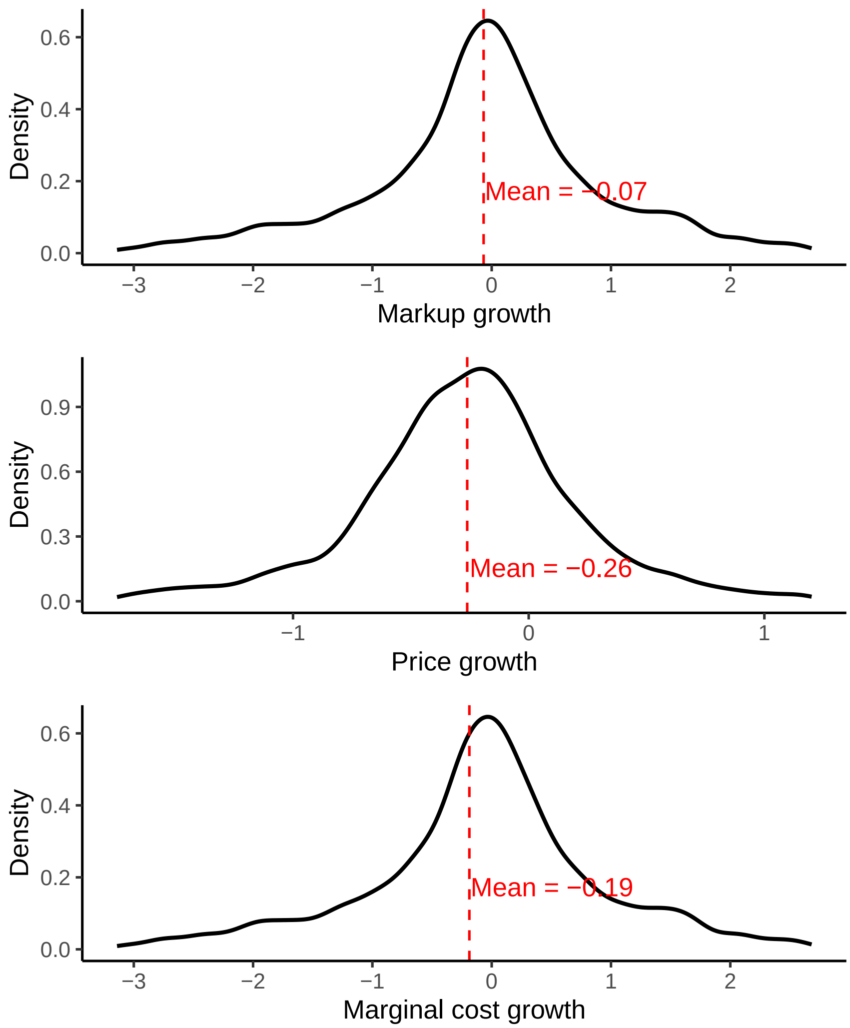
For Online Publication: Appendix

A Additional tables and figures

Figure A1: Change in markups, prices and marginal costs (1998-2008)



Notes: Figure A1 shows the growth of markups, prices and marginal costs for the same firm-product pairs from a pre-reform year (1998) to a post-reform year (2008). Outliers in the top and bottom third percentiles have been removed in each plot. The graph exploits within firm-product pair variation and shows that for manufacturing firms over this period, there is on average a 7% decline in markups, a 26% decline in prices compared to the consumer price index, and a 19% decline in marginal costs.

Table A1: Pre-reform industrial characteristics and patent reform exposure

Dependent Variables:	Change in output tariff	Change in input tariff	Export growth	Import growth
Model:	(1)	(2)	(3)	(4)
Patent intensity	-0.0052	7.66×10^{-5}	0.0243	-0.0471
	(0.0058)	(0.0020)	(0.0276)	(0.0330)
Observations	53	51	53	53
R^2	0.01570	2.88×10^{-5}	0.01498	0.03843

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The dependent variable *Change in output tariff* and *Change in input tariff* is the change in log of output and input tariff, respectively at NIC three-digit level between 1995 and 1999. *Export growth* and *Import growth* is the change in log aggregate exports from India and aggregate imports into India, respectively at NIC three-digit level between 1995 and 1999. The data for aggregate exports and imports is from UN COMTRADE database. The independent variable *Patent Intensity* is the average at NIC three-digit level of the patent intensity measure from EPO (2013). IID standard errors are reported in parentheses. $*$, $**$, $***$ show that the coefficient is statistically different from zero at 10, 5, and 1% level of significance.

Table A2: Pre-reform firm characteristics and patent reform exposure

Dependent Variables:	Output	R&D	Labour productivity
Model:	(1)	(2)	(3)
Patent Intensity	0.0051	0.0061	-0.0022
	(0.0069)	(0.0044)	(0.0041)
Observations	1,880	1,880	1,880
R^2	0.00028	0.00060	0.00013

Clustered (nic4) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

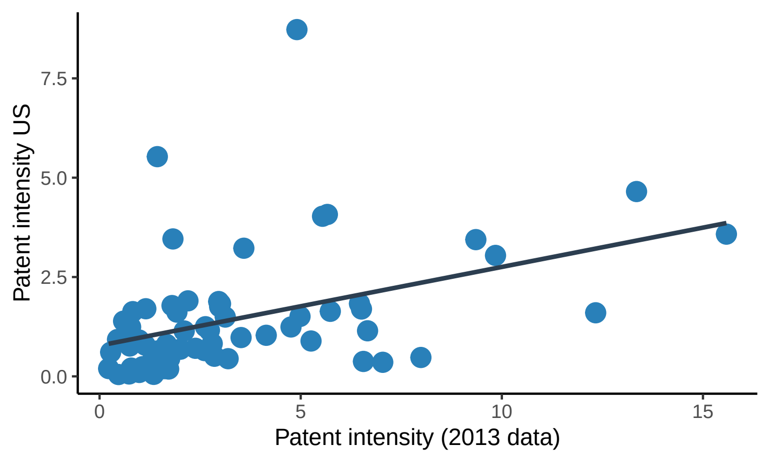
Note: The dependent variable *Output* is the pre-reform change in log of sales of a firm (between 1995 and 1999). *R&D* is the change in the inverse hyperbolic sine of R&D expenditure of a firm between 1995 and 1999. *Labour productivity* is the change in log of the ratio of total sales and estimated employment of a firm between 1995 and 1999. The independent variable *Patent Intensity* is the weighted average of the patent intensity for a firm, as estimated in equation 1. Standard errors (in parentheses) are clustered at four-digit NIC level. $*$ 10%, $**$ 5%, $***$ 1% significance level.

Table A3: Summary Statistics: Exposure to the patent reform

Variable	Mean	SD	Min	Max
Panel A: **At firm level**				
Patent intensity	2.953	3.779	0.697	15.583
Patent intensity-US	1.064	1.287	0.000	8.727
Panel B: **At product level**				
Patent Intensity	3.267	4.043	0.697	15.583
Patent Intensity-US	1.110	1.329	0.000	8.727

Note: The table provides summary statistics for two measures of patent intensity for the data used in firm-level analysis (Panel A) and firm-product level analysis (Panel B). Patent Intensity is the number of patents per 1000 employees for four-digit NIC industries from EPO and Patent Intensity-US is the number of patents per unit of sales (multiplied by 100) for four-digit NIC industries from USPTO and Compustat. At firm level, the patent intensity measures are weighted (see equation 1).

Figure A2: Correlation between European and US industry level patent intensity



Note: Patent Intensity is the number of patents per 1000 employees for four-digit NIC industries from EPO and Patent Intensity-US is the number of patents per unit of sales (multiplied by 100) for four-digit NIC industries from USPTO and Compustat.

Table A4: Using absolute values of patent applications and R&D

Dependent Variables:	Patent applications	R&D expenditure	Patent applications	R&D expenditure
Model:	(1)	(2)	(3)	(4)
	OLS	OLS	Poisson	Poisson
Post * Patent Intensity	0.0967***	7.390***	0.0847**	0.1255***
	(0.0332)	(2.084)	(0.0387)	(0.0324)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	40,997	40,997	4,332	18,102
R^2	0.48196	0.49689		

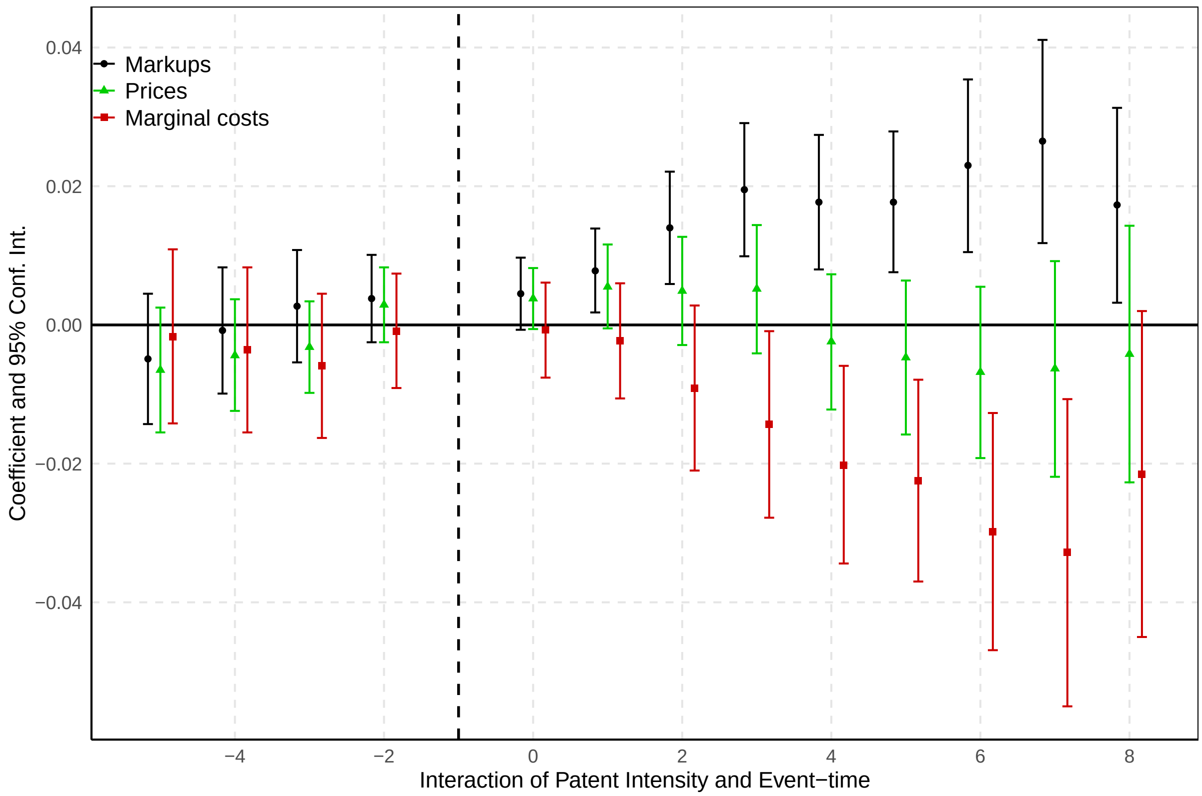
Note: The dependent variable *Patent applications* is the number of patent applications of a firm in a given year, and *R&D expenditure* is the R&D expenditure of a firm in a given year. The independent variable *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level

Table A5: Changes in markups conditional on marginal cost

Dependent Variable:	Log markups	Log markups
Model:	(1)	(2)
	OLS	IV
Post*PatentIntensity	0.0106	0.0090
	[-.0040, .0276]	[-.0086, .0261]
Log marginal cost	-0.633***	-0.634***
	[-.7191, -.532]	[-.7665, -.4727]
Log marginal cost- Square	0.0128**	0.0007**
	[.0011, .0259]	[.00083, .03645]
Log marginal cost- Cube	0.0006**	0.0006**
	[.00004, .0012]	[.00003, .00153]
Firm-Product-Unit	Yes	Yes
Year-Industry	Yes	Yes
Observations	75480	63442
R^2	0.648	

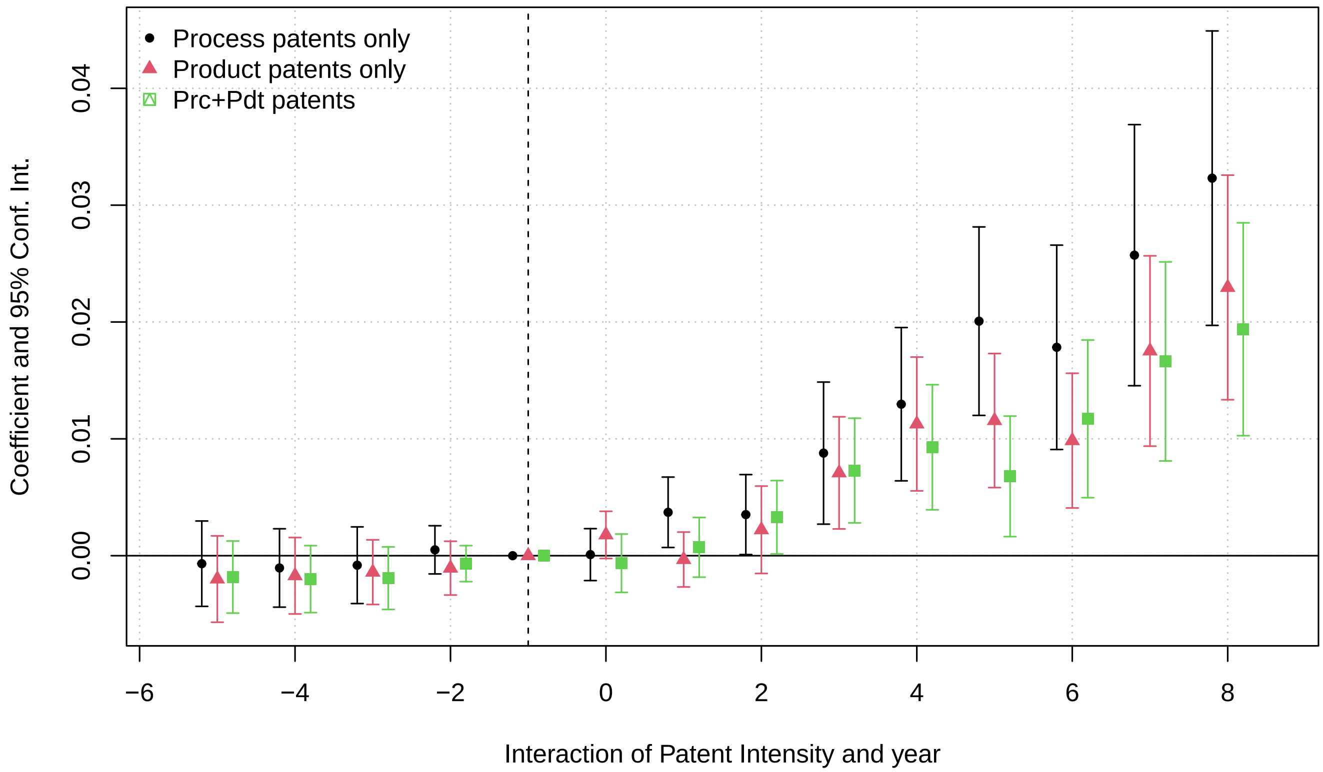
Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016). *Log marginal costs* is the difference of log of prices and log of estimated markups. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Column (2) uses the lag values of marginal cost to instrument marginal cost. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Figure A3: Markups, prices, and marginal costs: At firm level



Note: The dependent variables *Markup index* and *Price index* are the log of the index of markup and prices at firm-level, and *Marginal-cost index* is the difference of price index and markup index. The index is created following Smeets and Warzynski (2013). Event-time 0 refers to year 2000 for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and year 2003 for all other firms. $PatentIntensity$ is the time-invariant firm-level exposure to the reform as defined by equation 1. The regression controls for firm and industry-time fixed effects. Confidence intervals are based on bootstrapped standard errors clustered at firm level.

Figure A4: Dynamic effect by type of patent



Note: The dependent variables *Process patents only*, *Product patents only* and *Product + Process patents* is the inverse hyperbolic sine of the number of the type of patent applications filed by a firm in a given year. Event-time 0 refers to year 2000 for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and year 2003 for all other firms. *PatentIntensity* is the time-invariant firm-level exposure to the reform as defined by equation 1. The regression includes firm and industry-time fixed effects. Standard errors are clustered at firm level.

Table A6: Economic profits

Dependent Variable:	Economic profit
Model:	(1)
Post * Patent Intensity	0.0295**
	(0.0127)
Fixed-effects	
Firm	Yes
Year-Industry	Yes
Observations	40,333
R^2	0.68221

Note: The dependent variable is the inverse hyperbolic sine of economic profit of a firm in a given year, where economic profit is equal to total sales minus labour, material, and capital costs (0.8 times gross fixed assets). *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

Table A7: Material prices

Dependent Variables:	Log of raw material prices
Model:	(1)
Post * Patent Intensity	-0.0071
	(0.0082)
Fixed-effects	
Firm-Raw Material	Yes
Year-Industry	Yes
Observations	129,727
R^2	0.88279

Note: The dependent variable in Column (1) is the price of raw materials used by a firm in a given year. *Post* equals one for year 2000 for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and year 2003 for all other firms, and *PatentIntensity* is the time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors are reported in parentheses, and are clustered at firm level. Significance level: * 10%, ** 5%, *** 1%

Table A8: Patents and R&D: Adding industry controls

Dependent Variables:	Patent applications	Is Patent applicant	R&D expenditure	Does R&D
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0164***	0.0069***	0.0249***	0.0004
	(0.0034)	(0.0013)	(0.0084)	(0.0022)
Input tariff	0.1033	0.0099	0.1795	-0.1403
	(0.3376)	(0.1007)	(0.5784)	(0.1348)
Output tariff	-0.0134	-0.0014	0.1682**	0.0695*
	(0.0207)	(0.0106)	(0.0682)	(0.0398)
FDI reform	0.1041***	0.0363***	0.2396***	0.0311
	(0.0380)	(0.0137)	(0.0808)	(0.0204)
Delincensing	0.0409	0.0129	0.0791	0.0225
	(0.0347)	(0.0146)	(0.0737)	(0.0252)
Tax credit	-0.0007	-0.0003	-0.0002	-1.16×10^{-5}
	(0.0007)	(0.0003)	(0.0022)	(0.0008)
Total Exports	0.0190**	0.0078**	-0.0144	-0.0107
	(0.0090)	(0.0039)	(0.0240)	(0.0085)
Total Imports	-0.0071	-0.0007	0.0047	0.0004
	(0.0056)	(0.0024)	(0.0185)	(0.0055)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	40,880	40,880	40,880	40,880
R^2	0.55677	0.42433	0.81324	0.75572

Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in a given year. *Input tariff* and *Output tariff* are time-varying tariff on inputs and outputs, respectively, *FDI reform* is a dummy for years after which the FDI rules within an industry were relaxed, *Delicensing* is a dummy for years after which industrial licenses were removed in an industry, *R&D tax credit* is the value of R&D tax credit applicable for an industry over time, *Total exports* and *Total imports* are the aggregate exports and imports for a three-digit industry in India in each year. All industry level variables are weighted using the product mix of firms in a year. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

Table A9: Markups, prices, and marginal costs: Adding industry controls

	Log markup (1)	Log prices (2)	Log marginal cost (3)
Post*PatentIntensity	0.0199***	0.0016	-0.0183***
	[.0066, .0451]	[-.0115, .0207]	[-.0429, -.0091]
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	75111	75111	75111
R^2	0.77944	0.96996	0.93113

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. The regressions control for the following controls: *Input tariff* and *Output tariff* are time-varying tariff on inputs and outputs, respectively, *FDI reform* is a dummy for years after which the FDI rules within an industry were relaxed, *Delicensing* is a dummy for years after which industrial licenses were removed in an industry, *R&D tax credit* is the value of R&D tax credit applicable for an industry over time, *Total exports* and *Total imports* are the aggregate exports and imports for a three-digit industry in India in each year. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Figure A5: Dynamic effect with industry controls

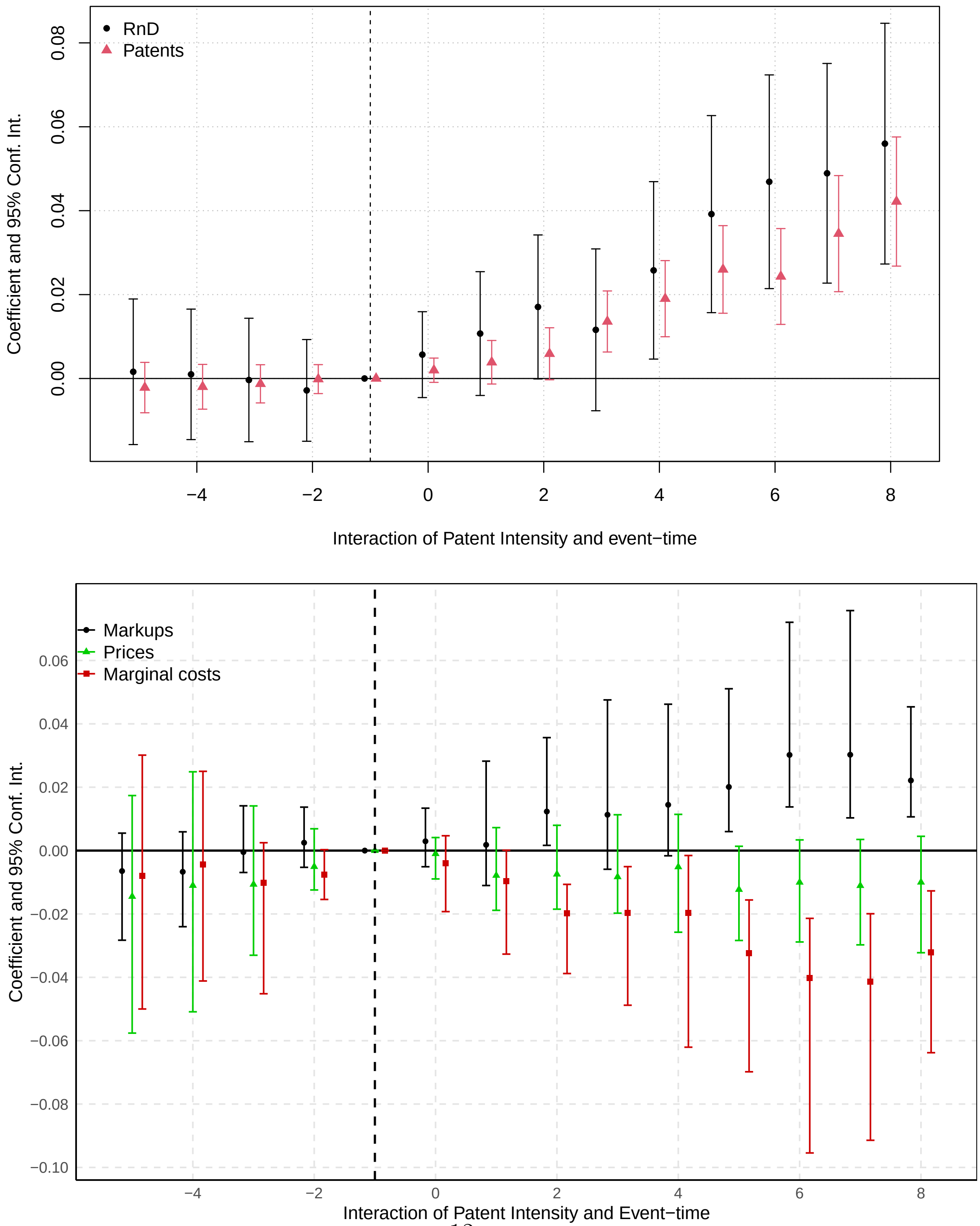


Table A10: Patents and R&D: Adding firm-level controls

Dependent Variables:	Patent applications	Is Patent applicant	R&D expenditure	Does R&D
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0217***	0.0090***	0.0400***	0.0038*
	(0.0042)	(0.0015)	(0.0091)	(0.0021)
Post × Foreign owned	-0.0580*	-0.0333***	-0.1095	-0.0108
	(0.0326)	(0.0125)	(0.1027)	(0.0266)
Post × Large firm	0.1100***	0.0490***	0.2149***	0.0614***
	(0.0170)	(0.0070)	(0.0464)	(0.0141)
Post × Does R&D pre reform	0.0512***	0.0246***	0.0179	-0.1733***
	(0.0116)	(0.0055)	(0.0428)	(0.0146)
Post × Is Exporter	0.0046	0.0048	0.0889***	0.0270**
	(0.0067)	(0.0033)	(0.0266)	(0.0117)
Post × Is Importer	-0.0006	0.0022	0.0423	0.0191
	(0.0065)	(0.0033)	(0.0284)	(0.0117)
Post × Import-sales ratio	0.0003***	0.0001***	0.0009***	0.0002***
	(5.94×10^{-6})	(2.09×10^{-6})	(1.76×10^{-5})	(5.45×10^{-6})
Post × Export-sales ratio	0.0131	0.0037	0.0039	-0.0004
	(0.0113)	(0.0033)	(0.0108)	(0.0031)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	38,937	38,937	38,937	38,937
R^2	0.53852	0.41687	0.81186	0.76016

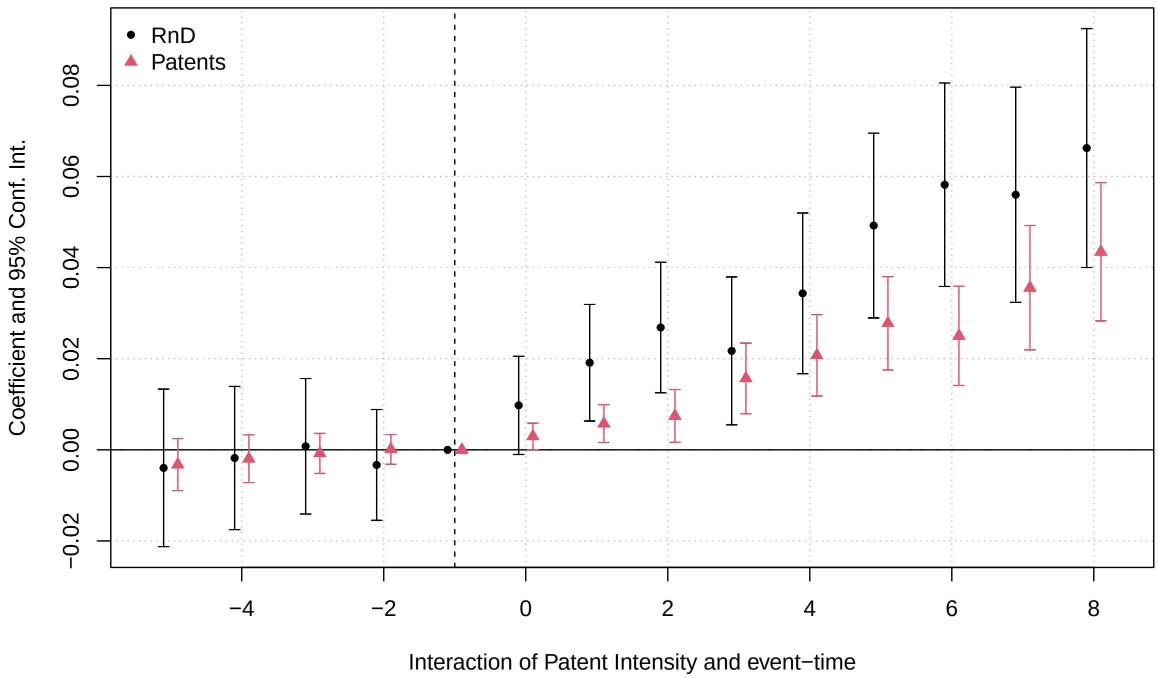
Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in any pre-reform year. *Large firm* is a dummy for whether the firm was large, defined as firms belonging to fourth quartile of the distribution of total assets, *Foreign owned* is a dummy for whether the firm was foreign owned, *Does R&D pre-reform* is a dummy for whether the firm engaged in R&D, *Is exporter* is the firm export status dummy, *Is Importer* is the firm import status dummy, *Export-sales ratio* and *Import-sales ratio* measure the the export-sales ratio and import-sales ratio. All the firm variables are measured prior to the reform. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. $PatentIntensity$ denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

Table A11: Markups, prices, and marginal costs: Adding firm-level controls

	(1) Log markup	(2) Log prices	(3) Log marginal cost
Post*PatentIntensity	0.0220***	0.0036	-0.0184**
	[.0131, .0356]	[-.0235, .0260]	[-.0547, -.0002]
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	69263	69263	69263
R^2	0.77757	0.96821	0.92691

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. The table controls for the following firm-level characteristics: *Large firm* is a dummy for whether the firm was large, defined as firms belonging to fourth quartile of the distribution of total assets, *Foreign owned* is a dummy for whether the firm was foreign owned, *Does R&D pre-reform* is a dummy for whether the firm engaged in R&D in any pre-reform year, *Is exporter* is the firm export status dummy, *Is Importer* is the firm import status dummy, *Export-sales ratio* and *Import-sales ratio* measure the the export-sales ratio and import-sales ratio. All the firm variables are measured prior to the reform. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Figure A6: Dynamic effect with firm-level controls



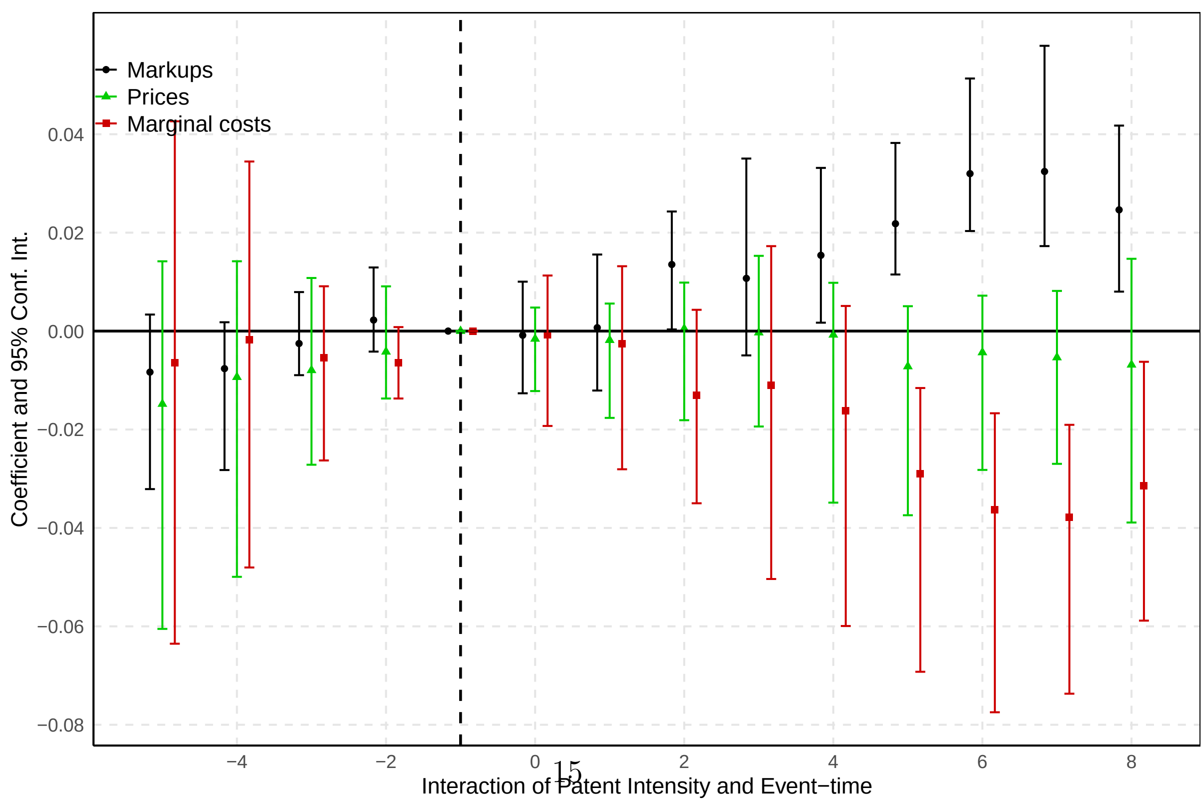


Table A12: Patents and R&D: Controlling for firm specific pre-trends

Dependent Variables:	Patent applications	Is Patent applicant	R&D expenditure	Does R&D
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0193***	0.00777***	0.0244*	0.00108
	(0.00389)	(0.00148)	(0.0139)	(0.00530)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	40,997	40,997	40,997	40,997
R^2	0.4477	0.3282	0.7006	0.6999

Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in a given year. The dependent variables are demeaned by an estimated fitted trend for firms using pre-reform observations. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. Patent Intensity is the time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. Significance level: * 10%, ** 5%, *** 1%

Table A13: Markups, prices, and marginal costs: Controlling for firm-product specific pre-trends

	Log markup (1)	Log prices (2)	Log marginal cost (3)
Post*PatentIntensity	0.0332**	-0.0212*	-0.0503**
	[.0041, .04778]	[-.0624, .0121]	[-.0908, -.0062]
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	75480	75480	75480
R^2	0.7619	0.9238	0.8447

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. The dependent variables are demeaned by an estimated fitted trend for firm-products using pre-reform observations. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Table A14: Patents and R&D: US-based measure of patent intensity

Dependent Variables:	Patent applications	Is Patent applicant	R&D expenditure	Does R&D
Model:	(1)	(2)	(3)	(4)
Post × Patent Intensity - US	0.0303***	0.0136***	0.0535***	0.0039
	(0.0083)	(0.0034)	(0.0207)	(0.0063)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	40,997	40,997	40,997	40,997
R^2	0.55148	0.42052	0.81207	0.75527

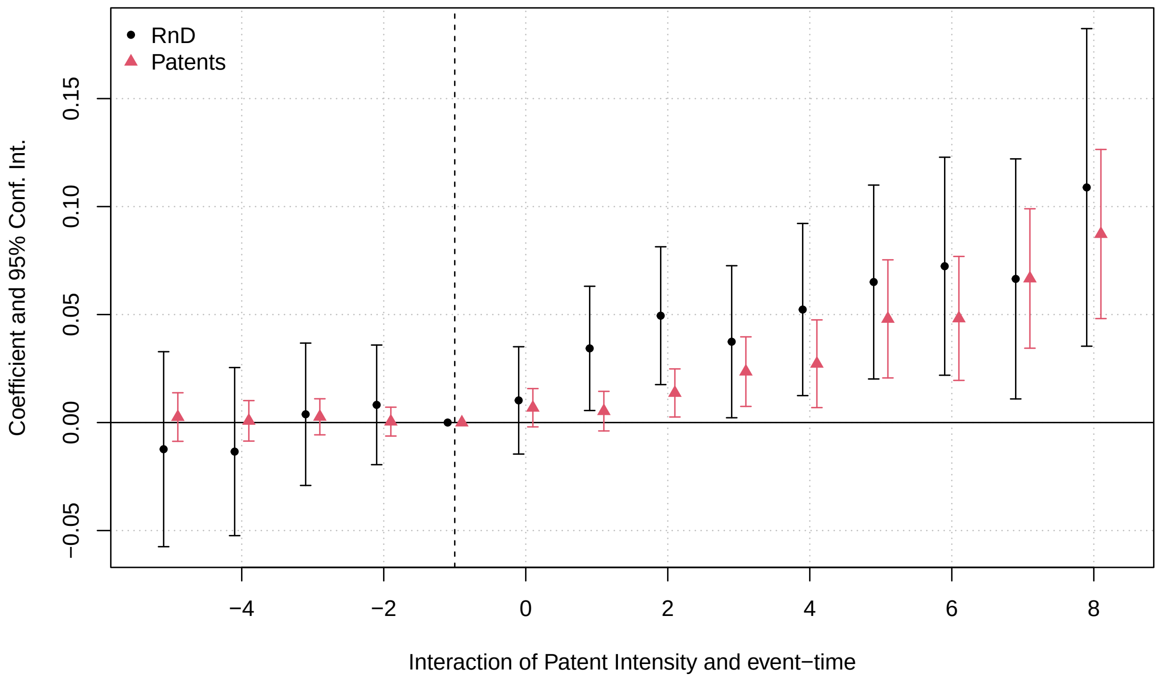
Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, *Is Patent applicant* is a binary variable equal to one for firms that file atleast one patent in a given year, *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year, and *Does R&D* is a binary variable equal to one for firms that spend on R&D in a given year. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. Patent Intensity-US is the time invariant firm-level exposure to the reform measured using the number of patents per unit of sales (multiplied by 100) for four-digit NIC industries from USPTO and Compustat data. Standard errors (in parentheses) are clustered at firm level. Significance level: * 10%, ** 5%, *** 1%

Table A15: Markups, prices, and marginal costs: US-based measure of patent intensity

	(1) Log markup	(2) Log prices	(3) Log marginal cost
Post × Patent Intensity-US	0.0396	-0.0339	-0.0735***
	[-.0200, .0990]	[-.1112, .0195]	[-.1338, -.0408]
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	75480	75480	75480
R^2	0.77939	0.96973	0.93087

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. Patent Intensity-US is the number of patents per unit of sales (multiplied by 100) for four-digit NIC industries from USPTO and Compustat data. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Figure A7: Dynamic effect: US-based measure of patent intensity



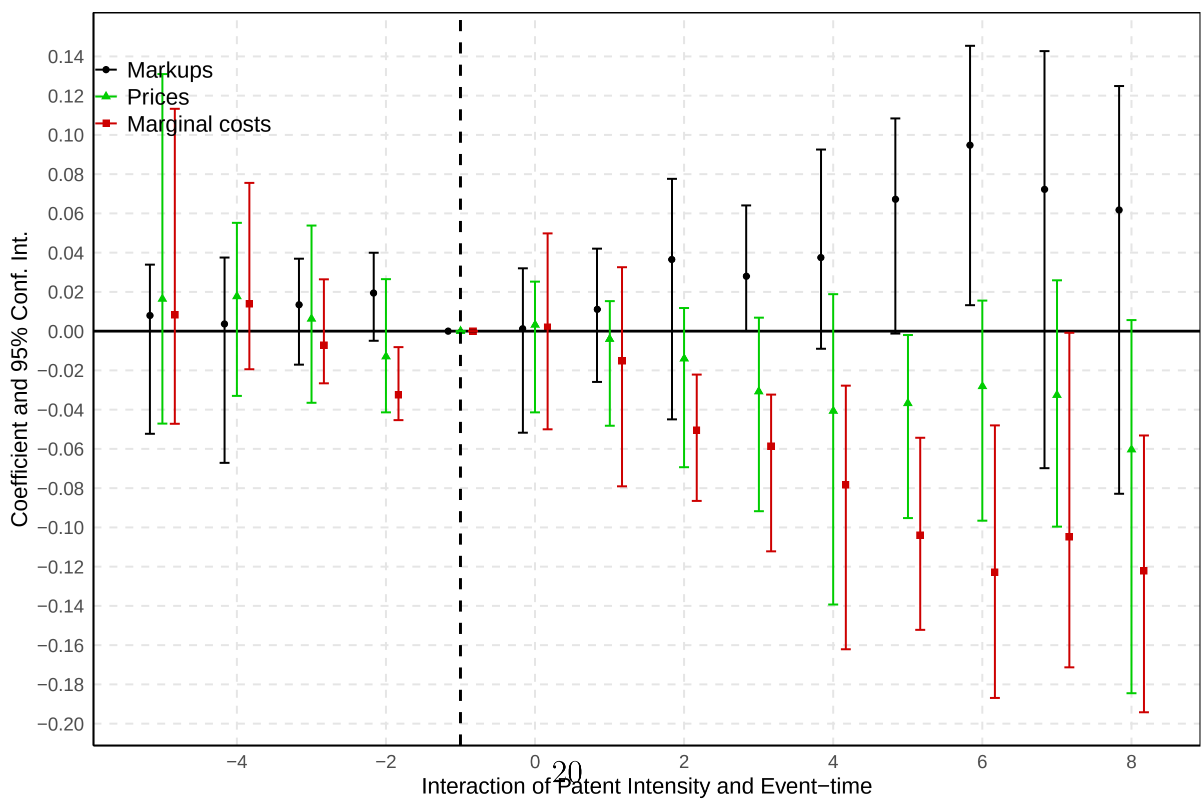
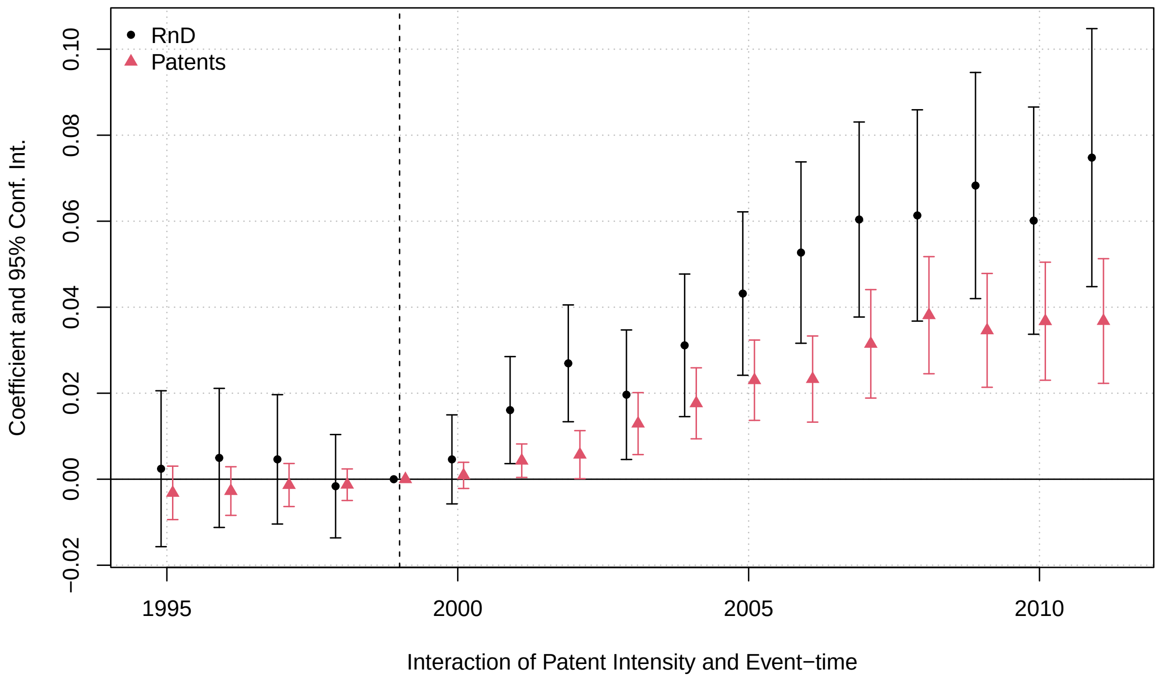


Figure A8: Dynamic effect: Defining financial year 2000 as the year of reform



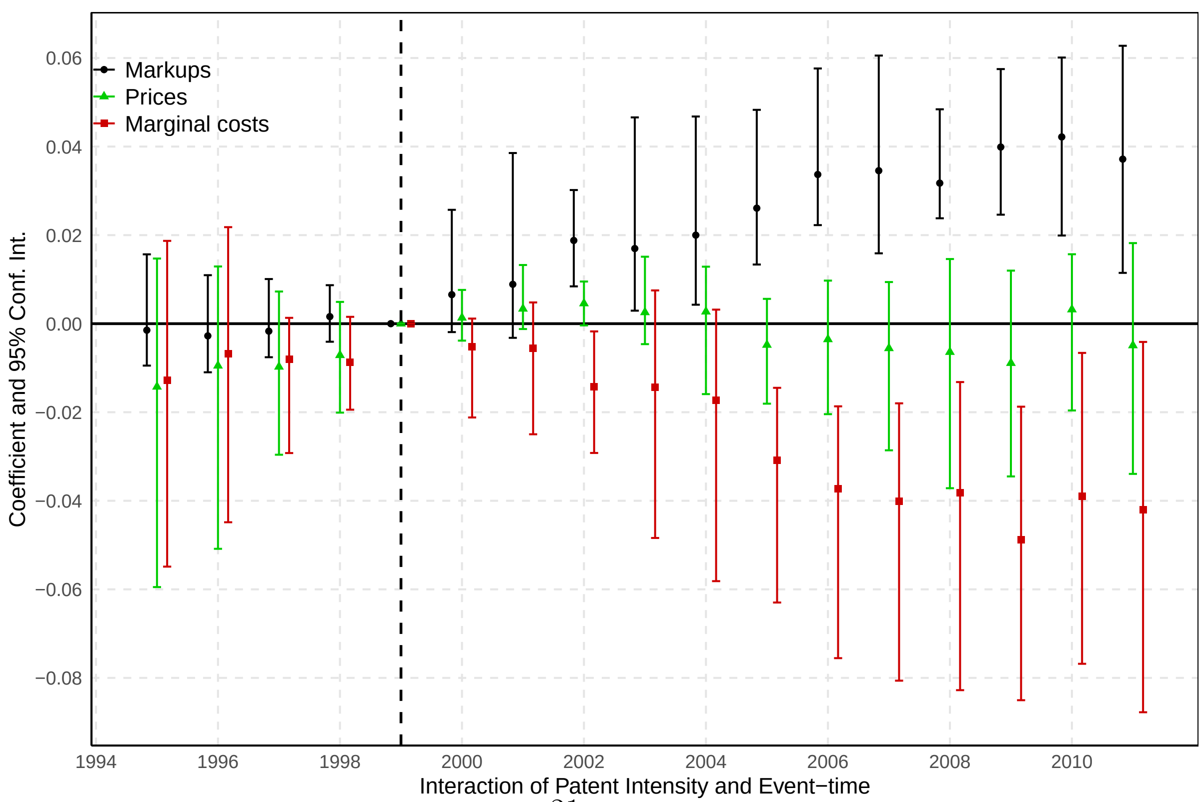


Table A16: Markups, prices, and marginal costs: Trimmed data

	Log markup (1)	Log prices (2)	Log marginal cost (3)
Post*PatentIntensity	0.0197***	0.0057	-0.0139**
	[.0076, .0408]	[-.0139, .0290]	[-.0484, -.0010]
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	72257	72257	72257
R^2	0.76985	0.97164	0.92801

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. All dependent variables are trimmed at 1% on both tails, and a common sample is used for all the three variables. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Table A17: Markups and marginal costs: Alternative production function estimation

	Controlling for R&D and patents		Cobb-Douglas	
	Log markup (1)	Log marginal cost (2)	Log markup (3)	Log marginal cost (4)
Post*PatentIntensity	0.0217***	-0.0179**	0.0227**	-0.0190**
	[.0132, .0320]	[-.0422, -.0069]	[.0045, .0316]	[-.0386, -.0008]
Firm-Product-Unit	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	74145	74145	74261	74261
R^2	0.78777	0.93320	0.83513	0.94618

Note: The dependent variables in column (1) and (2) are log of markups and marginal costs where we control for R&D and patents in the Markov process. Cobb-Douglas Markup is the markup and marginal costs estimated using a Cobb-Douglas production function. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. *PatentIntensity* is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Table A18: Patents and R&D activity: By firm size

Dependent Variables:	Patent applications	R&D expenditure	Process patents	Product patents
		Panel A: Small		
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0075*	0.0171*	0.0043	0.0047**
	(0.0040)	(0.0089)	(0.0029)	(0.0023)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	16,911	16,911	16,911	16,911
R^2	0.50859	0.70634	0.52005	0.36217

Dependent Variables:	Patent applications	R&D expenditure	Process patents	Product patents
		Panel B: Large		
Model:	(1)	(2)	(3)	(4)
Post * Patent Intensity	0.0315***	0.0522***	0.0226***	0.0152***
	(0.0063)	(0.0133)	(0.0049)	(0.0037)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes	Yes
Observations	24,086	24,086	24,086	24,086
R^2	0.56769	0.81026	0.52197	0.51951

Note: The dependent variable *Patent applications* is the inverse hyperbolic sine of the number of patent applications of a firm in a given year, and *R&D expenditure* is the inverse hyperbolic sine of the R&D expenditure of a firm in a given year. *Process patents* and *Product patents* is the inverse hyperbolic sine of the number of the type of patent applications filed by a firm in a given year. In Panel A, *Small* refers to firms whose pre-reform sales is less than the median sales of a four-digit NIC industry, and in Panel B, *Large* refers to the above median firms. The four-digit NIC code here is the code assigned to the firm by Prowess, and it remains the same for a given firm during our sample period. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* denotes time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors (in parentheses) are clustered at firm level. * 10%, ** 5%, *** 1% significance level.

Table A19: Markups, prices, and marginal costs (firm-level indices): By firm size

	Log markup	Log prices	Log marginal cost
		Panel A: Small	
Post * Patent Intensity	0.00956	0.00305	-0.00651
	(0.00666)	(0.00817)	(0.0105)
Firm	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	16911	16911	16911
R^2	0.60903	0.64928	0.63000

Variable	Log markup	Log prices	Log marginal cost
		Panel B: Large	
Post * Patent Intensity	0.0172**	0.00268	-0.0145*
	(0.00528)	(0.00529)	(0.00700)
Firm	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	24086	24086	24086
R^2	0.53218	0.66870	0.58763

Note: The dependent variables *Log Markup* and *Log prices* are the log of the index of markup and prices at firm-level, and *Log Marginal-cost* is the difference of price index and markup index. In Panel A, *Small* refers to firms whose pre-reform sales is less than the median sales of a four-digit NIC industry, and in Panel B *Large* refers to the above median firms. The four-digit NIC code here is the code assigned to the firm by Prowess, and it remains the same for a given firm during our sample period. *Post* equals one from 2000 onwards for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and equal to one for all other firms from 2003 onwards. *PatentIntensity* is the time-invariant firm-level exposure to the reform as defined by equation 1. Standard errors are bootstrapped standard errors clustered at firm level. * 10%, ** 5%, *** 1% significance level.

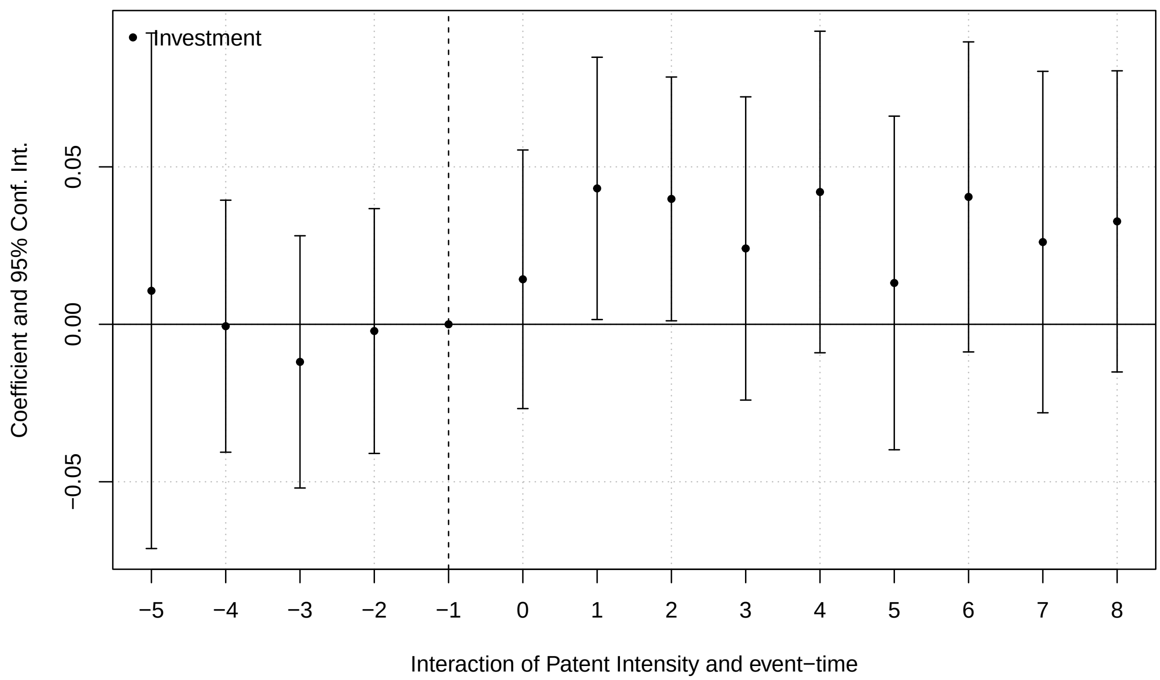
Table A20: Markups, prices, and marginal costs: By pre-reform industry concentration

Dependent Variables:	Log markup	Log prices	Log marginal cost
	Panel A: High concentration		
Model:	(1)	(2)	(3)
Post * Patent Intensity	0.0386***	-0.0003	-0.0389*
	[.0202, .0755]	[-.0245, .0387]	[-.0746, .0009]
Fixed-effects			
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	25,163	25,163	25,163
R^2	0.79887	0.97797	0.94520

Dependent Variables:	Log markup	Log prices	Log marginal cost
	Panel B: Low concentration		
Model:	(1)	(2)	(3)
Post * Patent Intensity	0.0232**	0.0061	-0.0171
	[.0103, .0406]	[-.0175, .0427]	[-.0379, .0101]
Fixed-effects			
Firm-Product-Unit	Yes	Yes	Yes
Year-Industry	Yes	Yes	Yes
Observations	50,317	50,317	50,317
R^2	0.76971	0.96261	0.91952

Note: The dependent variable *Log markup* is the log of firm-product-unit level markups estimated following De Loecker et al. (2016), *Log prices* is the unit price reported in Prowess for each product sold by a firm, and *Log marginal costs* is the difference of log of prices and log of estimated markups. Panel A shows the results for product groups where the Hirschmann-Herfindahl Index (HHI) is less than the median HHI index across 4-digit NIC products in the pre-reform period, and Panel B shows the above median product groups. The independent variable *Post* equals one from 2000 onwards for pharmaceuticals and chemicals, and equal to one for all other four-digit NIC groups from 2003 onwards. $PatentIntensity$ is the four-digit NIC group level measure of patents per 1000 employees. Wild cluster bootstrap confidence intervals are reported in brackets. Clustering is at NIC four-digit level. Significance level: * 10%, ** 5%, *** 1%

Figure A9: Effect on capital investment



Note: The dependent variable, capital investment, is the inverse hyperbolic sine of a one-year change in a firms' gross fixed assets. Event-time 0 refers to year 2000 for firms whose largest share of sales prior to the start of the reform is from pharmaceuticals or chemicals, and year 2003 for all other firms. $PatentIntensity$ is the time-invariant firm-level exposure to the reform as defined by equation 1. The regression includes firm and industry-time fixed effects. Standard errors are clustered at firm level.

B Details on robustness tests

In this section, we assess the robustness of our findings by incorporating controls for additional policy changes in India throughout our sample period. Furthermore, we account for firm characteristics that may be correlated with the exposure of the firm to the reform. We also examine the sensitivity of our results to employing an alternative measure of patent intensity at the four-digit industry level.

Controlling for other policy changes in India

While the empirical strategy uses detailed variation in the reliance on patenting across four-digit industries to identify the effect of the reform, a concern could be that other major reforms that were initiated in India since the 1990s could drive the results if they also happened to affect the patent-intensive industries more. To test if $Post \times PatentIntensity$ is capturing the effect of other reforms, we control for other policy changes that took place during our period of study and potentially had industry-specific effects.

Prior to 1985, an industrial license was required in India to establish a new factory, significantly expand capacity, start a new product line, or change location of a factory. Most industries were delicensed by 1995, and only a few were delicensed after. We use the data collected by (Aghion et al., 2008) to control for the timing of delicensing post 1995 for three-digit NIC industries. Second, as documented by Topalova and Khandelwal (2011), trade reform started in India with the balance of payment crisis in early 1990s, and tariffs were slashed from an average of 97% in 1989 to 47% in 1995 . Although a significant share of the reduction in tariffs happened prior to 1995, tariffs continued to decrease at a varying rate for different industries during the sample period of this study. We augment our regression with the annual input and output tariffs applicable for three-digit NIC industries. Following the previous literature, output tariffs are measured as average MFN rates across products by 3-digit industry. Input tariffs are output tariffs weighted by input-output coefficients. We also include the annual value of exports and imports at three-digit NIC industry level in our regression to account for aggregate changes in international market access during this period. Third, India also deregulated limits and approvals required for foreign direct investment since the early 1990s. We follow Bau and Matray (2023) and create a binary variable equal to one for a five-digit industry for the years during which FDI in that industry was either granted automatic approval or the cap on investment was increased to at least 51%. Finally, following Ivus et al. (2021) we control for the value of R&D tax credit applicable to different two-digit industries in a given year. Further details on the calculation of these variables is available in Appendix C.

Since all these policy changes vary at the industry-year level, for our firm-level analysis, we create a weighted measure at firm-level using the product mix of firms prior to the initiation of the reform. First, we augment equations (2) with the measures of policy changes defined above at the firm-level. Table A8 shows that the results for the effect on patenting and R&D are robust to the inclusion of other policy changes. The coefficients remain similar to the baseline. The results also suggest that deregulation of FDI investment was associated with higher firm-level patenting and R&D investment during our sample period.

Results for markups, marginal cost and prices are shown in Table A9. Here we augment equation (4) with the industry-time varying measures of policy changes mapped to firm-products. The effect of the reform on markup and marginal costs remains robust to controlling for these policy changes. The coefficients remain similar to the baseline. Finally, Figure A5 shows the dynamic effect for firm- and product-level outcomes, and shows that the baseline results are robust to controlling for other policy changes.

Controlling for pre-reform firm characteristics

In the baseline, we estimate exposure to the reform at the firm-level using a sales-weighted measure of patent intensity for the product mix sold by firms prior to financial year 2000. To allay concerns that this measure of exposure could be capturing some other firm characteristics along which firms with a patent-intensive product mix differ, we augment the baseline regression (equation 2) with firm characteristics measured prior to the reform and interact them with *Post*. We control for whether the firm was large, defined as firms belonging to fourth quartile of the distribution of total assets, whether the firm was foreign owned, whether the firm engaged in R&D, its export status, its import status, the export-sales ratio and import-sales ratio prior to the reform.

Results for patenting and R&D are shown in Table A10. We find that the coefficient on $Post * PatentIntensity$ for the number of patent applications, the likelihood of patenting, R&D expenditure, and with the augmented regression, also for the likelihood of doing R&D, is positive and statistically significant. The value of the coefficients, if anything, becomes larger as compared to the baseline estimation in Table 2. Along with the baseline results, we find that large firms, those that were already investing in innovation prior to the reform, and exporting/importing firms also seem to patent more and invest in R&D after the reform.

Table A11 shows the results for product-level outcomes while controlling for firm-level characteristics interacted with *Post*. We find that markups increase post reform within firm-product-groups most exposed to the reform, and that the increase in markups is driven by a decline in marginal costs. The coefficients are similar to the baseline results in Table 4. Finally, we show the dynamic effect of the reform controlling for firm-level characteristics in Figure A6 for firm- and product-level outcomes. The results remain similar.

To account for potentially differential trends across firms and firm-products, we follow the two-step strategy suggested by Goodman-Bacon (2021) and first fit trends for each unit using pre-reform observations only. In the second step, we rerun our regressions with outcome variables demeaned by the estimated fitted trend from the first step regression. The results are documented in Table A12 and A13. These specifications confirm our previous results and even indicate higher effects on markups and marginal costs as compared to our baseline specification.

Defining and measuring exposure to the reform

As discussed in section 3.3, we use an alternate measure of exposure to the patent reform based on patent applications filed by listed US firms. We utilize the four-digit NAICS industry classification of firms in Compustat to calculate the total number of patents filed within each industry. To normalize the total number of patent applications, we use total firm sales within an industry since number of employees information in Compustat is incomplete. Subsequently, we harmonize the NAICS classification with the NIC four-digit classification available for Prowess data. Given that Compustat data is only available for publicly listed firms in the United States, we prefer using the measure from EPO (2013) for our baseline specification. Figure A2 shows that there is a high correlation in industry-level measure of patent intensity when using European data from EPO (2013) and US data as described above, suggesting that cross-industry reliance on patenting as an appropriation mechanism is similar across geographies.

Using this measure, we study the effect of the reform on firm patenting and R&D outcomes following equation (2). Results in Table A14 confirm that the reform had a positive and significant effect on the patenting intensity of firms, the likelihood of patenting, and on R&D expenditure. The estimates indicate that relative to firms producing products that don't rely on patenting, firms in product markets with the average level of patent intensity (1.064) increase the number of patent applications by 4% and R&D expenses by 6.6%. Thus, the economic magnitude too is quite comparable to the baseline results.

In Table A15, we show the estimated effect of the reform on markups, prices and marginal costs using the US based measure of exposure to stronger patent protection. We find qualitatively similar results. Post reform, there is a significant decline in average marginal costs. Prices do not fall one to one with declining costs implying higher markups, although the latter effect is not statistically significant. Relative to products that don't rely on patenting as an appropriation mechanism, the marginal costs of product groups with mean patent intensity (1.109) drops by 8% post reform, but prices drop by only 3.7%. Finally, we show the dynamic effect using the US based measure of exposure to the patent reform in Figure A7 for firm- and product-level outcomes. The results remain qualitatively similar for both firm- and product-level outcomes.

To account for the fact that the patent reform was initiated in financial year 2000, we use a non-staggered approach where-in we define financial year 2000 as the first year of reform for all industries. Figure A8 shows that the results for all main outcome variables are robust to using a common timing of reform for all industries.

C Data description

C.1 Patent matching

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

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 also use firm address from Prowess and applicant address given in patent data to determine the quality of matches in cases where the name match is not sufficient.

In addition to matching patents to firms, we attempted to match patents directly to the products produced by a firm. The exercise yielded numerous unmatched patents due to several factors. Establishing a concordance between International Patent Classification (IPC) classes and product codes is complex and not straightforward. Additionally, there exists a significant lag, one that is likely to vary by industry, between the year of patent application filing and the year in which the invention appears in the product mix of firms, if it appears at all. Further, many patents can be relevant for more than one product category.

C.2 Defining product and process patents

We follow Banholzer et al. (2019) to identify whether a patent is a product or a process patent using the following keywords: a) For process patents, the keywords include method, process, procedure, use, utlilis(z)ation, and usage b) For product patents, the keywords include device, machine, material, tool, apparatus, vehicle, compound, composition, substance, and article. We count the keywords in the title, abstract, and claims of each patent application, and identify a patent as a product or a process patent as follows. We first use the share of process patent keywords in the abstract of a patent to classify patents as follows: if the share is greater that 2/3, we call the patent a process patent, if it is less than 1/3, we call it a product patent, and if it is between 1/3 and 2/3, then we say it is mixed patent. We use abstracts for the classification because they provide more information than the title, and because information on claims is not readily available from the Indian Patents Office. We use text search tools to identify claims from the complete specification of the patent. However, whenever abstract information is not available or the abstract is less than 15 characters, we use the share of process patent keywords first from claims and then from the title, respectively to classify patents.

Out of 10594 patents that are matched to our sample of firms from CMIE Prowess between 1995 and 2011, 3943 are classified as process patents, 3831 are classified as product patents, 1892 are classified as a mixed patent, and 928 are unclassified due to lack of data.

Examples of process patents below show that cost-reduction is an imperative part of such applications:

- *Intelligent hot metal detector* by Tata Steel Ltd. in 2006

  > "...reduced overall cost of hot metal detection in a confined area"

- *Improved process for preparing an edible product* by Hindustan Unilever Ltd. in 2003

  > "...a process for producing particulate common salt of high flow characteristics by way of a cost-effective and simple process of manufacture."

- *A cost effective process for production of (benzhydryloxy)-dimethylethylamine and salts* by Wanbury Ltd. in 2007

- *A Brake Disc Assembly for Automobiles* by Tata Motors Ltd. in 2010

  > '...simplifies the casting and the number of machining processes reduced to manufacture the brake disc and further reduces the weight and the cost of manufacturing of the brake disc."

- *A system and method for reducing the discharge temperature and thereby cooling the hot compressed air through energy conservation* by CTR Manufacturing Industries Ltd in 2007

The examples above show that a surge in process patents after the reform can explain a part of the decline in marginal costs we observe for firm-products most exposed to the reform.

C.3 Measurement of other reforms

Trade tariffs: Information on output tariffs is taken from WITS (World Integrated Trade Solution) To estimate the input tariffs, we use the input-output tables for India from the Ministry of Statistics and Programme Implementation, Government of India.[28] We use input output tables for the financial years, 1993-94, 1998-99, 2003-04, and 2007-08. We hand-map NIC 2008 3 digit codes to the commodity and industry codes in the input-output table, and aggregate the input-output coefficients to the 3 digit NIC code level. To obtain the input tariff in industry i, we multiply the output tariffs for a given NIC industry j with the ratio of input usage for that industry j in industry i.

Aggregate exports and imports: We source annual Export and import value at six-digit Harmonised System (HS) code level from UN Comtrade, and harmonise the data to HS 1992 version. We map HS 1992 code to three-digit NIC 2008 and create an annual measure of exports and imports.

FDI: We define a dummy for product groups where FDI was liberalised in a given year following Bau and Matray (2023). An industry is coded as having been liberalised if a policy change occurred that allowed automatic approval and/or increased the cap on investments to at least 51% of capital (though, in some cases, the maximum is higher).The reform is concentrated in 2001 and 2006.

Delicensing: Prior to 1985, an industrial license was required to establish a new factory, significantly expand capacity, start a new product line, or change location (see Hazari (1967); Bhagwati and Desai (1970)). This allowed the government to allocate planned production targets to firms. We borrow our measure of delicensing from Aghion et al. (2008). In 1985, around one-third of all three-digit industries were delicensed. The second wave of reform was launched in 1991. Industrial licensing was practically abolished in 1991. Very few industries were delicensed after 1995, the start of our sample period, and we account for the timing of delicensing in these

[28]We use the commodity-industry coefficient matrix from MOSPI.

industries.

R&D tax credit: We follow Ivus et al. (2021), and identify the percentage of tax credit applicable to different industries during our sample period. All industries had an applicable tax credit of 100 since the 1990s, however during 1998 and 2001, there was an increase in tax credits for certain industries. We use a time-varying value of tax credits by two digit industry groups to control for the effect of tax credits.

D Estimation of markups and marginal costs

To estimate markups, and marginal costs, we follow the methodology introduced by De Loecker et al. (2016), henceforth LGKP. This method accounts for endogeneity of productions inputs similar to standard techniques in the productivity literature (Ackerberg et al., 2015; Levinsohn and Petrin, 2003; Olley and Pakes, 1996). In addition, it relies on the availability of quantities and prices at the product level to separate physical from revenue based productivity. As most (if not all) firm-product-level data sets, Prowess does not include complete information on prices of all inputs and has no information about how inputs are allocated across products for multi-product firms. The LGKP approach uses a control function for unobserved input prices and a method to recover the allocation of inputs across products. We describe the methodology below.

The basis for productivity estimation is the logarithmic version of the production function described in section 3.2 with an additive error term, ϵ_{ijt}, which captures measurement error:

$$q_{ijt} = f_k(\boldsymbol{v}_{ijt}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{6}$$

where $\boldsymbol{v}_{ijt}$ denotes a vector of logarithmic physical inputs (capital k_{ijt}, labor l_{ijt} and materials m_{ijt}) allocated to product j and ω_{it} is the log of TFP. For our application, we use a translog production function, hence:

$$f_j(\boldsymbol{v}_{ijt};\boldsymbol{\beta}) =\beta_l l_{ijt} + \beta_m m_{ijt} + \beta_k k_{ijt} + \beta_{lm} l_{ijt} m_{ijt} + \beta_{lk} l_{ijt} k_{ijt} + \beta_{mk} m_{ijt} k_{ijt} \\ + \beta_{ll} l_{ijt}^2 + \beta_{mm} m_{ijt}^2 + \beta_{kk} k_{ijt}^2 + \beta_{lmk} l_{ijt} m_{ijt} k_{ijt} \tag{7}$$

The translog production function yields a physical output-material elasticity:

$$\theta_{ijt}^M = \beta_m + \beta_{lm} l_{ijt} + \beta_{mk} k_{ijt} + 2\beta_{mm} m_{ijt} + \beta_{lmk} l_{ijt} k_{ijt} \tag{8}$$

which varies across firms within industries and nests a Cobb-Douglas production function as a special case.

Physical inputs can be expressed as $v_{ijt} = \rho_{ijt} + \tilde{v}_{it} - w_{ijt}$ where $\tilde{v}_{it}$ denotes observed input expenditures at the firm-level, ρ_{ijt} is the log of the input share allocated to product j and w_{ijt} denotes the log of an input price index (defined as deviations from industry-specific deflators). When the log of input allocations, ρ_{ijt}, is captured by a function $A(\rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta})$ and the log of the unobserved input price index, w_{ijt}, are captured by a function $B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta})$, output can be rewritten as a function of firm-specific input expenditures instead of unobserved product-specific input quantities (see LGKP for the exact functional form of $A(.)$ and $B(.)$ for the translog case):

$$q_{ijt} = f_j(\tilde{\boldsymbol{v}}_{ijt};\boldsymbol{\beta}) + A(\rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{9}$$

Estimation of the parameters of the production function is based on a sample of single product firms for which $A(.)$ can be ignored. Unobserved input prices w_{it} in $B(.)$ are approximated by output prices (p_{it}), market shares (s_{it}), product dummies ($\boldsymbol{D_j}$),and export status (ex_{it}) to account for differences in product quality and local input markets. In some specifications, we also include the number of patents and R&D expenditures, which we collect into a vector $\boldsymbol{I}_{i,t-1}$, as we want to allow for the possibility that these variables are associated with changing input prices.

Material demand is assumed to be a function of productivity, other inputs, output prices, market share, product and export status and, in some specifications, additional controls ($\boldsymbol{I}_{it}$), hence: $\tilde{m}_{it} = m(\omega_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p_{it}, \boldsymbol{D}_j, s_{it}, ex_{it}, \boldsymbol{I}_{it})$. Inverting the material demand function yields and expression for productivity: $\omega_{it} = h(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{c}_{it})$ where $\boldsymbol{c}_{it}$ includes all variables from the input demand function except input expenditures.

The use of single product firms induces a further complication of endogenous sample selection since single-product firms might be less productive compared to multi-product firms. Analogous to the exit correction proposed by Olley and Pakes (1996), the probability of remaining a single product firm (SP_{it}) is a function of previous year's productivity and an unobserved productivity cut-off. SP_{it} is predicted from a Probit regression of a dummy variable for remaining a single-product firm on $\tilde{\boldsymbol{v}}_{i,t-1}$ $\boldsymbol{c}_{i,t-1}$, investment, year and industry dummies, and, in specifications with patents and R&D, $\boldsymbol{I}_{it}$.

For the evolution of productivity, the following law of motion is assumed:

$$\omega_{it} = g(\omega_{i,t-1}, ex_{it}, SP_{it}, \boldsymbol{I}_{it}) + \varsigma_{it} \tag{10}$$

We allow the evolution of productivity to depend on export status and the probability of remaining a single product firm, and sometimes innovation-related variables $\boldsymbol{I}_{i,t-1}$.

Since for single product firms, we do not face the problem of unobserved input allocation across products and can drop the product-specific subscript of the production function, equation (9) becomes:

$$q_{ijt} = f(\tilde{\boldsymbol{v}}_{ijt}; \boldsymbol{\beta}) + B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{11}$$

One can combine $f(.)$, $B(.)$ and $g(.)$ into a function $\phi(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{c}_{it})$ such that output can be expressed as a function of observable variables and measurement errors:

$q_{it} = \phi(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{c}_{it}) + \epsilon_{it}.$

$\phi(.)$ is approximated by a linear combination of all its elements and a polynomial in all continuous variables. While this expression does not identify any parameters of the production and input price functions, it identifies output net of measurement error ϵ_{it} which is denoted by $\hat{\phi}_{it}$. Productivity can then be expressed as:

$$\omega_{it} = \hat{\phi}_{it} - f(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) - B(\boldsymbol{c}_{it}, \boldsymbol{c}_{it} \times \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}, \boldsymbol{\delta}) \tag{12}$$

where $\boldsymbol{\delta}$ are the parameters of the input price function to be estimated. For identification of parameters, equation (10) can be used to construct moment conditions:

$$E[\varsigma_{it}(\boldsymbol{\beta}, \boldsymbol{\delta})\boldsymbol{Z}_{it}] = 0 \tag{13}$$

$\boldsymbol{Z}_{it}$ is a vector which includes current values of labour and capital, lagged values of materials and their higher order and interaction terms as they appear in the production function. It further includes lagged values of market shares and prices as well as interactions of lagged prices with lags of production factors and market share. We treat labor as a dynamic input that is characterized by adjustment costs due to the rather rigid Indian labor market. Estimation is undertaken using the GMM procedure suggested by Wooldridge (2009) which is based on moment conditions on the combined error term $\varsigma_{it} + \epsilon_{it}$.

This estimation procedure yields estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$, hence, it identifies all parameters from the production and input price functions. We estimate $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ separately for each industry to allow for industry-specific production technologies and input prices. Under the assumption that $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are the same for multi- and single-product firms within industries, input allocations across products within multi-product firms can be recovered which allows estimation of markups and marginal costs for each firm-product-year. Note that as discussed by LGKP, this assumption does not rule out differences in productivity levels between single- and multi-product. Since

Table A21: Estimation of production function by sector

Sector	θ_l	θ_k	θ_m	RTS
Coke	0.06	0.10	0.87	1.05
Computers, electronics, machinery	0.28	0.19	0.68	1.18
Food, beverages, tobacco	0.21	0.13	0.80	1.31
Metals (basic and fabricated)	0.13	0.11	0.80	1.09
Motor vehicles, transport	0.21	0.24	0.63	1.08
Non-metallic minerals	0.19	0.36	0.46	0.98
Pharma, chemicals	0.24	0.18	0.70	1.14
Rubber	0.18	0.24	0.72	1.16
Textiles, apparel, leather	0.12	0.14	0.76	1.05
Wood, paper, printing	0.18	0.10	0.77	1.04

productivity is modelled to be factor-neutral, differences in TFP do not imply differences in $\boldsymbol{\beta}$ or output elasticities. The approach also allows for TFP to depend on the number of products which can imply (dis)economies of scope. Under the assumption of a common production technology within industries, one can express predicted output as: $\hat{q}_{ijt} = f(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{\beta}, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{it}$, and divide the production function into two parts, f_1 and f_2, such that only f_2 depends on input allocations across products. This yields a system of equation for each firm-year which allows identifying productivity ω_{it} for each firm-year and the input share allocation ρ_{ijt} for each firm-product-year:

$$\begin{aligned} \hat{q}_{ijt} - f_1(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{\beta}, \hat{w}_{ijt}) =& f_2(\tilde{\boldsymbol{v}}_{ijt}, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{it} \\ \sum_j \exp(\rho_{ijt}) =& 1 \end{aligned} \tag{14}$$

Table A21 shows the average estimated output elasticities and returns to scale by sector.

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