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Does Change in Intellectual Property Rights Induce Demand for Skilled Workers? Evidence from India[1]

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Abstract: *Do incentives to innovate create demand for skilled workers more than proportionately? We study the question using the implementation of the Patent (Amendment) Act in India in 2002 to comply with the Trade-Related Intellectual Property Rights agreement. We find, first, stronger intellectual property protection has a sharper impact on demand for skilled workers for high patentable industries. Demand for skilled workers increased by 0.5%–2.9% for industries that are more patentable. The average compensation for skilled workers went up by 10% in high patentable industries but decreased for unskilled workers by about 2%. Second, the increase in wage inequality can partly be attributed to the increase in wages rather than incentives. Third, the increase in demand for skilled workers is due to both the increase in intensive margin (or price) and extensive margin (number). Fourth, the aggregate effect is completely driven by industries producing intermediate goods and big plants. Finally, the reforms led to a significant reallocation of resources between industries. The high patentable industries invested more in technology adoption, started to produce more product varieties at higher quality, and filed for more product patent claims. Broadly, we demonstrate that stronger intellectual property protection leads to higher wage inequality between industries.*

Keywords: intellectual property regimes, wage inequality, highly patentable and less patentable industries, skilled workers

JEL classifications: D21, D23, L23, O1, O34

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1. Introduction

Adoption of technology and artificial intelligence has a significant global impact on firms. It is most visible when a firm demands different kinds of workers because more jobs are changing with technology adoption or innovation (Acemoglu and Restrepo, 2018; Jaravel, 2018). The rise in wage inequality between skilled and unskilled workers has spurred extensive discussions since the late 1970s (e.g., OECD, 2011; UNDP, 2013; ILO, 2016; World Bank, 2016). The current discussion on the disproportionate demand for skilled workers in relation to unskilled workers focuses mainly on structural changes driven by an increasingly connected global economy and its interaction with the rapid spread of digital technologies. In the wake of growing technological intensiveness of firms and higher innovative activities, unskilled workers around the globe face unprecedented pressure. Digital technologies replace jobs that used to be performed by unskilled workers, whilst complementing jobs and tasks performed by skilled workers. Subsequently, highly skilled workers are generally rewarded with greater compensation, which, in turn, causes a negative impact on income distribution between skilled and unskilled labour (OECD, 2011; World Bank, 2016).

Do stronger incentives for innovation affect wage inequality? This is the central question in our paper. The past couple of decades have experienced a sharp increase in wage inequality between skilled and unskilled workers, with demand for skilled workers increasing more than proportionately. For instance, the proportion of routine (low-skilled) labour in the United States (US) declined from 39% in 1968 to 23.6% to 1968 in 2013, whilst that of non-routine (skilled) labour saw an increase from 24.4% to 33.6% (Eden and Gaggl, 2014). Further evidence confirms these findings for several countries with different levels of technology (e.g. Srour et al., 2013; Marouani and Nilsson, 2016; Gaggl and Wright, 2017). This trend appears to be common in developed and emerging countries, contrary to the principle of comparative advantage (Berman and Machin, 2000; Kremer and Maskin, 2006; Maskin, 2015). Yet, no consensus has been reached as to the main underlying factors behind this increase. We argue that for an emerging country such as India, policy changes towards a stronger patent regime, because of globalisation, could be one such factor.

Although job markets in highly technology-diffused countries generally favour skilled workers, technological changes are not always skill-biased when we take into account the degree of substitutability and complementarity between technology and labour (Saint-Paul, 2008). Acemoglu (2002) emphasises that institutions and international trade can also influence patterns of wage inequality.[4]

We look at one such institutional factor: change in the regime of intellectual property rights (IPR) protection. Such economy-wide change could facilitate far-reaching impact on patterns of wage inequality through a higher proportion of technology adoption. We use the change in the IPR regime in India as an instrument to establish the causal effect of change in technology adoption on wage inequality. A strong IPR regime can be a powerful instrument to direct technology development. Greater IPR protection might induce greater technological change, which, in turn, would increase demand for skilled workers, with implications for wage inequality.

India's patent policy started to shift towards greater protection of IPR because of the emergence of the World Trade Organization (WTO) agreement on Trade-Related Intellectual Property Rights (TRIPs) after 1995. India had a 10-year transition period to implement a TRIPs-compliant IPR regime, but several inconclusive rounds of discussion ensued in parliament because of opposition (Reddy and Chandrashekaran, 2017). Eventually, parliament passed two acts – the **Patents (Amendment) Act, 1999** (1999 act) and the **Patents (Amendment) Act, 2002** (2002 act) – to comply with TRIPs. The acts amended all previous provisions outlined by the **Indian Patent Act, 1970** (1970 act).

However, India's Controller General of Patents, Design and Trademarks stated that the 2002 act (Government of India)[5] replaced all earlier patent rules implemented by the 1970 act.[6] The 2002 act provided the impetus to make the IPR

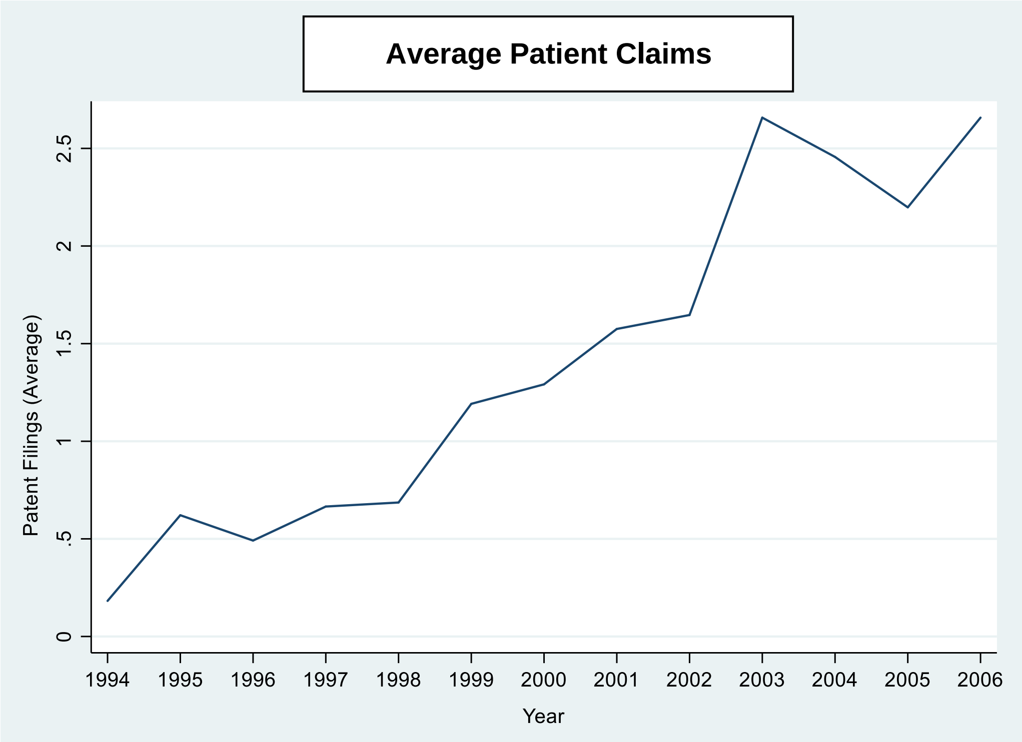
[4] A set of institutional mechanisms, which are outside this paper's scope, contribute to determining wage levels, such as the minimum wage law, unionisation, non-standard employment contracts, amongst others (Lemieux, 2008). Elements that increase the role of market forces to determine wages were adopted at the beginning of the 1980s by several conservative governments determined to decrease the role of wage-setting institutions, leaving wages to become more closely aligned with individual productivity. This was made possible, for instance, by declining unionisation and falling real value of the minimum wage. These wage-setting mechanisms complemented the skill-biased technical change hypothesis.

[5] The act came into force on 20 May 2003.

[6] The 1999 act provided for filing applications for product patents for drugs, pharmaceuticals, and agrochemicals, but applications were to be reviewed only after 31 December 2004. The act was a compromise in a still-uncertain environment for patent policy and came into effect after the failed Patent (Amendment) Bill, 1995. The 1999 act failed to encourage much innovation.

regime compatible with TRIPs patent laws. The act significantly broadened the scope for implementing a TRIPs-compliant IPR regime.[7]

Figure 1: Patent Claims: Indian Manufacturing Firms, 1994–2006



Note: Presents yearly average patent claims by a manufacturing firm in India, 1994–2006.
Source: Authors.

Figure 1 plots the number of patent claims by an average manufacturing firm from 1994 to 2006.[8] The figure demonstrates a sharp increase from 2002 onwards; an average firm filed for 1.5 patents before 2002 and 2.5 after the imposition of the 2002 act. For an average manufacturing firm, patent claims more than doubled after the imposition of the new patent laws (1999–2006). In 1994–2006, an average chemical and pharmaceutical firm had about 30% probability of filing for a patent, followed by machinery and equipment (21%); coke, refined petroleum products,

[7] It introduced the 'Bolar' exception, inspired by US law exempting manufacturers from infringement if they develop products, conduct research, and submit test data for regulatory purposes. A joint parliamentary committee submitted a report to the lower house. Whilst the committee's research was thorough, political circumstances ensured that the 2002 bill faced less difficulty than earlier legislation. Thus, 2002 act was passed . Three years later, India pushed the 2002 act with the addition of the compulsory licensing provision (Article 3[d]), and implemented the Patents (Amendment) Act, 2005 to comply with all the provisions of TRIPs (see Chatterjee et al. [2015] for more details on Article 3[d]).

[8] Based on a separate firm-level patent database from EKASWA (see section 4.5). Figure A.1 (Appendix A) plots total claims by manufacturing firms in 1994–2006 and shows a similar trend.

and nuclear fuel (17%); motor vehicles (13%); and tobacco products (8.5%).[9] We did not investigate the effect of patent claims on demand for skilled workers. We use a policy change that might have increased incentives for innovation and examined its effect on relative demand for skilled workers. We exploit patent claims data to show how innovation significantly increased after 2002.[10] An increase in incentives to establish a monopoly over products can drive firms to alter its workforce significantly.

We study how a large cross section of manufacturing firms responded to the 2002 act in changing compensation structure and its related components.[11] We use this specific policy change to investigate the effect of stronger IPR, brought about by the 1999 and 2002 acts, on the share of skilled manufacturing workers' wages.

Innovation policy affects compensation structure by encouraging technology adoption, which occurs through at least two channels. First, stronger patent protection can lead firms to invest in a range of activities that need intensive skilled labour or managerial talent, including research, conceptualisation, and development of new products, and product branding and marketing (Teece, 1986, 1994). Second, existing processes are pushed closer to the technology frontier by more research and development (R&D) expenditure, technology transfer, import of capital goods, amongst others. All these tasks can present firms with more complex problems and possibly raise the value of skilled workers such as managers as problem-solvers (Garicano, 2000). We expect to see a general expansion in demand for skilled workers as well as skilled workers' compensation.

Crucially, because skills and technology capital complement each other as innovation inputs, firms in highly patentable industries, such as chemicals or pharmaceuticals, will demand more skilled workers than others. Therefore, the increase in demand for skilled workers in highly patentable or high-technology

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[9] Figure A.2 (Appendix A) plots average claims across industries (2-digit level) in 1994–2006 and shows a similar trend. Table
B.1 (Appendix B) lists the probability of an average firm filing a patent across these industry categories.

[10] However, this could be a simple trend. We do not control for any other kind of simultaneous changes that may affect patent claims.

[11] By compensation structure, we mean total labour compensation of plants. In our case, compensation is equal to wages plus incentives.
Sometimes, we use compensation and wages interchangeably.

sectors can increase more than proportionately than in other industries. Our central hypothesis is that the increase in wage inequality between skilled workers (or managers) and others caused by IPR shock would be higher in highly patentable industries. Table 1 shows such was the case after the implementation of the 2002 act. The share of skilled workers in highly patentable industries rose by about 13% within 4 years (1999–2003) but only by 4% in other industries. The difference between the share of skilled workers in highly patentable industries and in others rose significantly in the same period.

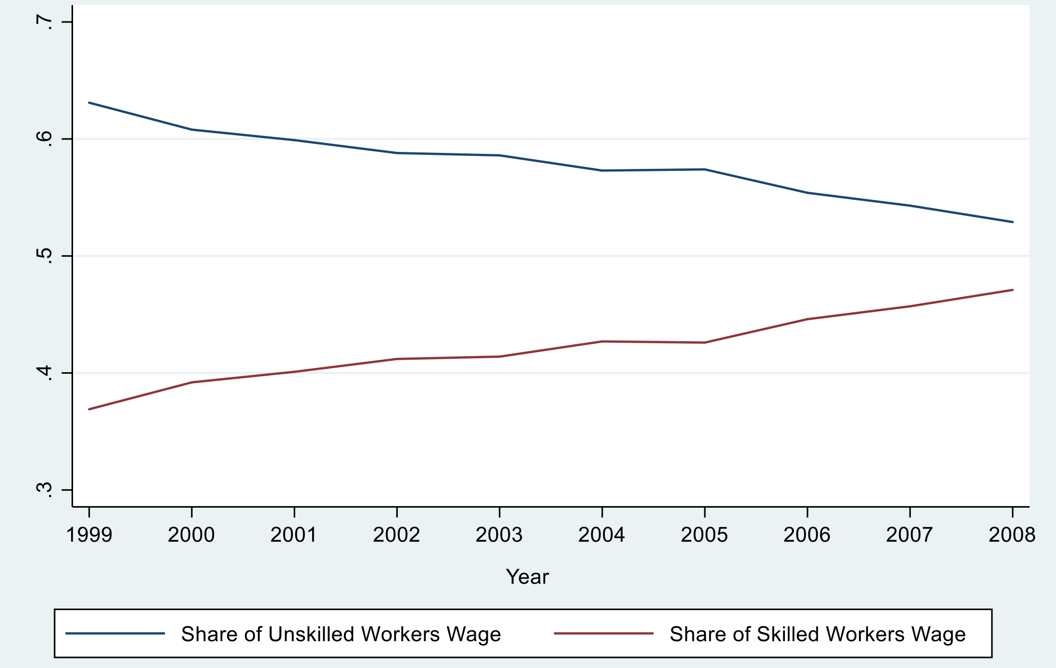
Table 1: Skilled Workers Wages: High- and Low- patentable Industries

Year	Skilled Workers' Wage Share		Difference
	High Patentable Industries	Low Patentable Industries	
1999	0.369	0.253	0.116**
2000	0.392	0.242	0.150***
2001	0.401	0.248	0.153***
2002	0.412	0.261	0.151***
2003	0.414	0.263	0.151***
2004	0.427	0.290	0.137***
2005	0.426	0.292	0.134***
2006	0.446	0.302	0.144***
2007	0.457	0.318	0.139***

Notes:
1. We use the definition by Delgado et al. (2013) to classify industries as highly and less patentable. Numbers represent average values of the share of skilled (or managerial) workers' compensation in total compensation of a plant across all the manufacturing industries in a representative year.
2. **Significant at the 5% level, ***Significant at the 1% level.
Source: Authors.

Figure 2 plots the share of skilled and unskilled workers' wages in highly patentable industries; the difference went down significantly within a few years. The share of unskilled workers' wages was 63% in 1999 and 52% by 2008. We argue that demand for skilled workers, which rose significantly more than for unskilled workers, especially in highly patentable industries, might partly be the result of the implementation of the 2002 act.

Figure 2: Share of Wages of Skilled and Unskilled Workers: High-patentable Industries, 1999–2008



Note: Figure presents the average share of a manufacturing industry in India, 1999–2008.
Source: Author.

Public policies might influence relationships between technology and labour. Patent policies are amongst the main elements that strengthen innovation and technological changes in developed and developing countries (OECD, 2013; 2014a, 2014b). IPR are amongst the most important institutional elements of patent policies, the strength of which impacts innovation, which, in turn, can lead to changes in the wage premium for skilled labour. Almost all the literature focuses on the welfare effect on skilled labour, such as change in skilled labour income, by exploring the direct impact of IPR or how IPR lead to spillovers and, in turn, impact skilled labour's income. One important issue that remains unresolved is the extent to which an IPR regime affects the wages of skilled labour and the return to capital and, thus, wage inequality.

The role of IPR protection in explaining the rate and direction of wage inequality has not been thoroughly analysed. This paper contributes to filling the gap. We investigate the effects of tightening protection of IPR on wage inequality between skilled (managerial) workers and unskilled (non-managerial) workers in India. We do so by answering the fundamental question: How do IPR protections affect relative demand for skilled labour and, possibly, wage inequality?

For our empirical exercises, we employ a plant-level panel dataset from the Annual Survey of Industries (ASI) for 1999–2007, provided by the Ministry of Statistics and Program Implementation. The dataset contains detailed data on labour compensation divided into managerial (skilled) and non-managerial (unskilled) components. The dataset provides data on capital employed, input expenditures, expenditure on computer equipment, and other important firm and industry characteristics. The panel format of the data enabled us to have a dynamic specification in which innovation and other firm decisions could affect demand for skilled workers.

Our results are clear and robust. Our main finding is that implementation of the 2002 act increased average compensation of skilled workers in highly patentable industries by about 10% but decreased average compensation of unskilled workers by 2%. Increase in demand for skilled workers is due to the increase in the intensive (price of the managers) and extensive (number of skilled workers) margins. Our results point to significant evidence of wage inequality between skilled and unskilled workers because of stronger incentives to innovate. Second, the increase in compensation of the skilled workers is due to the increase in the fixed component of compensation, which is wages. Third, demand for skilled workers is completely driven by industries producing intermediate inputs and the big firms.

The next section reviews the literature. Details about the data are in section 3. The empirical strategy and results are reported in section 4. We draw conclusions in section 5.

2. Literature Review

It has long been acknowledged (Rosen, 1981) that technology is a key driver of changes in wages and income (Saint-Paul, 2008; Goldin and Katz, 2009). The skill-biased technological change hypothesis is based on empirical evidence of a positive relationship between diffusion of computer use, particularly in job sites, and wage differentials between workers with low and high skills (Katz and Murphy, 1992; Autor et al., 1998). Mallick and Sousa (2017) found that technology is correlated with skill premium and demand for skilled labour, especially in science-based and production-intensive industries.

Skilled migration has been identified as an important indicator of technological change within the context of international relations. A large body of literature suggests that skilled labour provides inventions and emigration of skilled labour alters a country's capacity to innovate. Grubel and Scott (1966) first used the term 'brain drain' to explain the impact of the trend of skilled migration from developing countries in reducing the innovative capacity of source countries (Commander et al., 2004). Agrawal et al. (2011) found that emigration of skilled labour weakens local knowledge networks (the brain-drain effect) but also allows innovators to retain access to knowledge accumulated abroad (the brain-bank effect).

Whilst most of the literature considers market forces, few studies have explicitly considered the link between the institutional changes and skill premium. Pi and Zhou (2014, 2015) investigated the impact of institutions' quality on wage inequality. The literature has mainly focused on the role of institutions in general terms, without specifying how each institution affects inequality. We focused on a crucial change in IPR policy, as it is one of the most important institutional instruments that governments can use to enforce structural change across the institutional landscape.

Only recently, a number of studies have explored the link amongst IPR protection, skilled labour mobility, and innovation, starting from the literature on relationships between IPR protection and North–South trade (Lai and Qiu, 2003; Grossman and Lai, 2004) and IPR protection and outsourcing or offshoring (Antras and Helpman, 2004). This literature emphasises the possible benefits from a government's relative incentive to provide patent protection, which typically increases with its relative endowment of human capital (Grossman and Lai, 2004), and the benefits that North and South can derive from harmonising their IPR standards along with the North liberalising the goods market (Lai and Qiu, 2003). Outsourcing or offshoring has been shown to influence the skill premium in a way similar to technological change. Outsourcing or offshoring directly affects wages of unskilled workers, thus increasing wage inequality. When it happens in the service sector, however, outsourcing or offshoring has been shown to affect skilled labourers, as well (Bottini et al., 2007).

Mondal and Gupta (2008) analysed the conditions under which, within a North–South model, strengthening IPR protection may favour innovation in the South. McAusland and Kuhn (2011) showed how governments use IPR policy to attract the creators of intellectual property (IP). Chu and Peng (2011) developed a two-country R&D-based growth model in which strengthening patent protection in developing countries increases economic growth but also worsens income inequality. Finally, Naghavi and Strozzi (2015) show that IPR moderate the relationships between migration and innovation because they provide the knowledge required to stimulate domestic innovation in developing countries.

Aghion and co-authors (Aghion et al., 2019; Aghion et al., 2018a; Aghion et al., 2018b) showed that innovation induces income inequality across regions and within firms. For example, Aghion et al. (2019) used data (patent filings) on US states to show that top income inequality is (at least partly) driven by innovation. Bøler (2016) used an R&D tax credit scheme in Norway to demonstrate that innovation significantly increases demand for skilled workers and that increase in demand is due to change in within-firm skill-biased productivity growth. Whilst our idea is similar, we argue that between-industry inequality plays a larger role than within-firm inequality in explaining the increase in relative demand for managers. The increase is due to the difference in the rate of technology adoption by technological leaders and technological ladders. Kline et al. (2019) analysed how patent applications can induce inequality in worker compensation amongst US firms. Aghion et al. (2018b) showed similar evidence for Finnish firms. We complement this literature by analysing how wage inequality changes because of a shift in innovation policy.

3. Data

We use plant-level panel data obtained from the ASI, the principal source of industrial statistics in India. It covers the entire country and all factories registered under sections 2m(i) and 2m(ii) of the Factories Act, 1948: i.e. factories employing

10 or more workers using power, and those employing 20 or more workers not using power.

The survey's primary unit of enumeration is a plant or factory in the case of manufacturing. The ASI frame classifies industries into two sectors: census and sample. In the census sector, the data from all the factories employing 100 or more workers are collected on a complete enumeration basis. The remaining factories fall under the sample sector, for which data are collected by drawing a representative sample using sampling techniques. The ASI classifies each plant in the data into industry categories according to the National Industrial Classification (NIC), up to the 4-digit level of disaggregation.

The data contain detailed information on production-related factors such as output, fixed assets, inventories, working capital, inputs, employment, labour costs, raw materials, electricity, power and fuel consumption, state location, ownership, year of incorporation, amongst others. The ASI provides data on number of persons employed, person-days paid, wages and salaries, bonuses, contributions to employee welfare funds, amongst others. The data on number of persons employed are classified into two main categories: workers and supervisory and managerial staff, corresponding to blue-collar and white-collar employees. Data on workers are further detailed based on gender and on nature of employment (permanent or contractual). We utilised these aspects of the dataset to the fullest to understand several dimensions of wage inequality caused by a paradigm shift in innovation policy.

4. Innovation and Wage Inequality

4.1 Empirical Strategy

Higher incentives to innovate can induce firms to demand more managerial skill to maximise innovation potential, and this change could be more pronounced for highly patentable industries. Therefore, we investigated our central question by employing a differences-in-differences approach, treating the highly patentable industries as the treatment group and the rest as the control group. This allowed us to isolate the differential impact of the 2002 act on relative demand for skilled workers. We used the following equation:

$$x_{ijt} = \alpha_j + \alpha_t + \alpha_t^j + \beta_p\left(PatentAct_{2002} \times HPI_j\right) + X_{ijt} + \varepsilon_{ijt} \qquad (1)$$

x_{ijt} is the share of skilled workers' compensation in total compensation of a plant i in industry j at time t; we use this as our primary outcome of interest. To understand whether there is any sort of quality–quantity trade-off, we use the number of managers and/or skilled workers as a share of total employees of a plant as our outcome of interest. $PatentAct_{2002}$ is a year dummy variable; it takes value 1 if year is greater than 2002, since the 2002 act was implemented to comply with TRIPs obligations, and 0 otherwise. HPI_j is a dummy variable; it takes a value 1 if an industry j is a highly patentable industry according to Delgado et al. (2013) and 0 otherwise.

The highly patentable industry list is primarily based on 4-digit North American Industrial Classification System (NAICS) codes with above average IP intensity in the US (based on patents, trademark, or copyrights) (ESA-USPTO, 2012). To define the highly patentable group of industries, Delgado et al. (2013) matched the NAICS industries to the United Nations Commodity Trade Statistics Database (UN-COMTRADE) product categories in the Standard International Trade Classification (SITC), Revision 3. Using the International Standard Industrial Classification (ISIC), Revision 4 to match India's National Industrial Classification (NIC),[12] we matched 50%–55% of the industries.

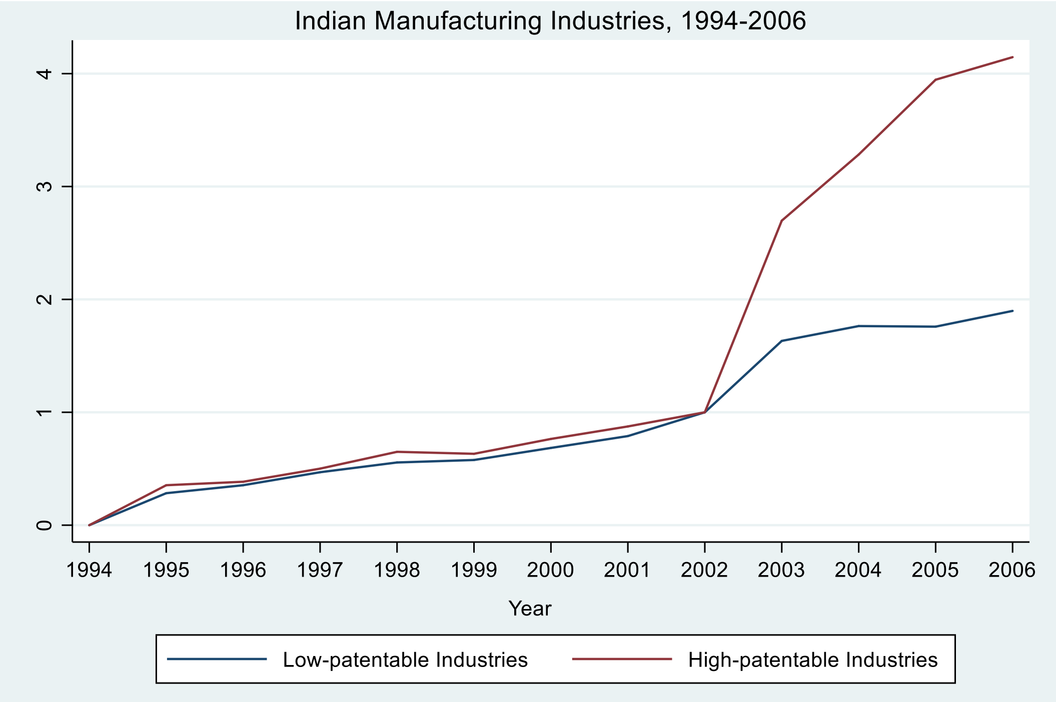
Our 'treated' group is composed of industries that are highly patentable or of high IP intensity and take a value 1 throughout the period of our study. The 'control' group is made up of industries that are less patentable or of less IP intensity and take a value 0. The identification of low-IP industries is based on the same classification described by the Economics and Statistics Administration and the United States Patent and Trademark Office (ESA-USPTO, 2012). Our conjecture is that, due to the implementation of the 2002 act, the patentable intensity of high-

[12] We used the UN classification system to match SITC, Revision 3 with 2004 NIC 4-digit industries and to classify the product categories into high-IP and low-IP products.

IP products would increase multifold, and so demand for skills would increase more than proportionately in those industries than in industries of low IP intensity. Our variable of interest is the interaction term, $PatentAct_{2002} \times HPI_j$. It captured the relative differences across the two sets of industries, where the classification is based on IP intensity of industry j (HPI_j).

We argue that imposing stronger patent rights will increase the probability of more patents being filed for highly patentable industries, and demand for skills, therefore, will be higher than in other industries. Figure 3 plots the normalised patent claims (in year 2002) by highly and less patentable industries. Both kinds of industries showed similar trends before 2002. Patent claims started to change or diverge significantly after 2002, however, with highly patentable industries unsurprisingly filing more patents than less patentable industries.

Figure 3: Patent Claims: High- and Low- patentable Industries, 1994 – 2006



Notes: Figure presents the normalized patent claims for manufacturing firms in India, 1994–2006.
Source: Authors.

β_p is the coefficient of interest. It measures the differential response of highly and less patentable industries due to IPR shock in terms of demand for skilled workers. IPR reform increased incentives to innovate. Skill is a strong complement to technological inputs (Garicano, 2000). Therefore, industries more likely to file for patents at the time of the reform demanded more skilled workers than those technologically less advanced. Acemoglu et al. (2006) argued that for countries closer to the technology frontier, selection of high-skill workers is crucial as skill is important for innovation. β_p measures between-industry inequality in terms of demand for skilled workers. We expect its sign to be positive.

Both types of industries are similarly affected by reform, which provides all industries the same incentives to innovate. This means that the effects we document are only due to the differential behavioural responses of the two types of industries. Our identification strategy is based on two assumptions. First, the behavioural responses of industries should not affect the timing and/or the occurrence of the reform; simply, reform is exogenous. Second, both types of industries should have had similar trends in patent claims before reform, on average. Figure 3 provides evidence for such.

X_{ijt} is a vector of firm- and industry-level characteristics that are likely to impact our outcome of interest – share of skilled workers' compensation. For example, following Chakraborty and Raveh (2018), we use input and output tariffs at the industry level to control for trade reforms initiated by the government during the 1990s. One other factor that could potentially affect demand for skilled workers is foreign direct investment (FDI). Apart from encouraging R&D and innovation, tighter IPR protection could also enhance foreign investors' confidence and, thus, attract more FDI. To the extent that FDI is more skill-intensive, the wage gap might increase. However, if FDI is not skill-intensive, the negative impact on the income gap due to technology adoption might be offset. We use industry–year trends and fixed effects to control for the interaction effect of stronger IPR protection and FDI flows into the economy.

India witnessed a significant information technology–enabled service (ITES) revolution during the 2000s, which could have increased skilled workers' compensation. We investigate whether there is a complementary effect of ITES and highly patentable industries. We control for other forms of product market competition effect (for domestic and export markets), management technology, labour regulation, productivity, amongst others. α_j is time-invariant industry and α_t year fixed effects.

Whilst estimating the above equation, we also carefully control for other simultaneous reforms, such as delicensing of industries (which happened during the 1990s), any unobservable possible tax incentives for R&D, and corporate governance reforms, amongst others, that might affect the share of skilled workers in a firm. If not controlled for, they might bias our outcomes. To control for these unobserved policy changes (or any other change in the economic environment affecting all firms), we used α_t^j – industry–year trends. We interact a firm's industrial classification at NIC 4-digit level (the most disaggregated level of industrial classification) with year trends to control for other simultaneous policy reforms that might affect our dependent variable.

4.2 Benchmark Results

Table 2 presents our benchmark results. We look at intensive and extensive margins of demand for skilled workers for 1999–2007 as our outcomes of interest, focusing primarily on intensive margin. Columns (1)–(8) show the result of the effect of the 2002 act on skilled workers' share of total labour compensation. Our results show that the coefficient of the interaction term $PatentAct_{2002} \times HPI_j$ is positive and highly significant across specifications.

Column (1) simply regresses the share of skilled workers' compensation on the interaction between the patent dummy and HPI_j, controlling for industry and year fixed effects. Our coefficient of interest is positive and significant. Column (2) introduces interaction between industry fixed effects and year trends. Column (3) interacts $PatentAct_{2002}$ dummy and industry fixed effects to control for the fact that certain industry characteristics might have driven the reform. For example, skilled workers in highly patentable industries might have lobbied for the 2002 act, which might have driven up their share of wages. Another worry with an interaction term such as $PatentAct_{2002} \times HPI_j$ could be that it is not HPI_j but some other omitted factor correlated with HPI_j that is driving plants' response to the 2002 act. To potentially control for that, we interact $PatentAct_{2002}$ with a key industry characteristic (sales) in column (4). Our coefficient of interest stays positive and highly significant; adding these interaction terms does little to change our benchmark result. It remains robust.

Table 2: Intellectual Property Rights Reform and Demand for Skilled Workers: Benchmark Results

	Skilled Workers' Compensation/Total Compensation								Skilled Workers/Total Employment	Average Compensation (Skilled)
						ATE	PPML	Change of Control Group		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$PatentAct_{2002} \times HPI_j$	0.007^{***}	0.007^{***}	0.029^{***}	0.023^{***}	0.010^{***}	0.053^{***}	0.017^{***}	0.003^{**}	0.033^{***}	0.095^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.006)	(0.001)	(0.009)	(0.006)
Constant	0.242^{***}	0.241^{***}	0.200^{***}	0.200^{***}	0.242^{***}	0.218^{***}	-1.435^{***}	0.240^{***}	-2.247^{***}	0.780^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.041)	(0.010)	(0.052)	(0.008)
R-square	0.122	0.122	0.076	0.075	0.124	n/a	0.123	0.122	0.187	0.140
N	289,723	289,723	289,723	289,723	289,723	289,723	289,723	289,723	289,406	288,520
Industry FE	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
HPI_j X Year FE	No	No	No	No	Yes	No	No	No	No	No
Industry FE X $PatentAct_{2002}$	No	No	Yes	No	No	No	No	No	No	No
Industry Output X $PatentAct_{2002}$	No	No	No	Yes	No	No	No	No	Yes	Yes
Industry FE(4-digit) X Year Trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes:

1. Columns (1)–(8) use share of skilled workers' compensation in total labour compensation of a plant, column (9) share of skilled workers in total employment of a plant, and column (10) average skilled workers' compensation (total compensation of skilled workers/total number of skilled workers) as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
3. Numbers in the parenthesis are robust clustered standard errors at the industry level.
4. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

In column (5), we interact the HPI_j with year dummies to control for the pre-trends that might have a strong influence on our results. We use the following regression equation:

$$\left(\frac{SkilledWorComp}{TComp}\right)_{it} = \alpha_j + \alpha_t + \alpha_t^j + \beta_p\left(PatentAct_{2002} \times HPI_j\right) + \alpha_t \times HPI_j + \varepsilon_{ijt}$$

Even controlling for pre-trends, our coefficient of interest was still positive and significant. The increase in demand for skilled workers in the intensive margin was due to the differences in the highly and less patentable industries after the imposition of the 2002 act. Our specifications show that because of the stronger incentives to innovate (due to the imposition of the 2002 act), demand for skilled workers increased by 0.7%–2.9% for highly patentable industries.

In column (6), we use simple average treatment effect, which measures the difference in mean (average) outcomes between the units assigned to the treatment (highly patentable industries) and control (less patentable industries) groups. We match industries based on size (sales) and capital employed. Our estimates suggest that the 2002 IPR reform increased relative demand for skilled workers between highly patentable and less patentable industries by 5.3% at the mean, which is significantly higher than our ordinary least squares (OLS) regressions.

Since our dependent variable is a ratio, estimating zero-valued variables with OLS might produce biased estimates. Following Silva and Tenreyro (2006), we use a Poisson pseudo-maximum likelihood (PPML) in column (7) to control for such. The PPML estimates the coefficients in percentage changes, and the dependent variable does not need to follow a Poisson distribution or be integer-valued (it can be continuous). As the point estimate demonstrates, the 2002 IPR reform continues to induce significant increase in the relative share of skilled workers' compensation.[13]

[13] We have also used ratio of the average wage of skilled workers to that of unskilled workers as the outcome of interest. The results are qualitatively highly similar.

Lastly, in column (8), we change our treatment and control group. The pre-1990s IPR regime was governed by the 1970 act, which aimed to prevent foreign monopolies.[14] Section 5 of the act states that, in the case of inventions (i) claiming substances intended for use or capable of being used as food or as medicine or drugs; or (ii) relating to substances prepared or produced by chemical processes (including alloys, optical glass, semiconductors, and inter-metallic compounds), no patent shall be granted in respect of claims for the substances themselves, but claims for the methods or processes of manufacture shall be patentable.

Although it seems, in view of the above two conditions, that apart from these three sectors, product patents were granted in other sectors before 2002, there were significant restrictions on them (Reddy and Chandrashekaran, 2017). For example, (i) many items apart from the chemical sector also involved significant use of chemical processes, such as textiles and leather, but the terms of patents were only 5–7 years whilst the international standard was 20 years; (ii) the government could use patented inventions to prevent scarcity or manage national emergencies; and (iii) costs of patent litigation were significantly higher in the absence of proper facilities. We follow section 5 of the 1970 act, and use the pharmaceuticals, chemicals, and food product sectors as a treatment group (and other manufacturing sectors as the control group) to show that the increase in skilled workers' compensation was much higher in the treatment group than in others. Our estimate shows that such is the case.

Column (9) focuses on the extensive margin of our outcome of interest: share of the number of skilled workers employed in total employment of a plant. We find a significant effect of the $PatentAct_{2002} \times HPI_j$ term; share of employment of skilled workers rose by 3.3%. This shows that the 2002 act significantly affected both the margins of demand for skilled workers. Following Garicano (2000), we can argue that the 2002 act might have induced production of new technology-intensive products, which led to the rise of non-routine problems in the production function to be solved by existing skilled workers and by new specialised skilled

[14] The 1970 act was partly based on the recommendations of the Patent Enquiry Committee (1948–1950) and the Ayyangar Committee (1957–59), which made two major observations: (i) the patent system had failed to stimulate and encourage the development and exploitation of new inventions for industrial purposes, and (ii) foreign patentees were acquiring patents not in the interest of the domestic economy but to protect an export market from competition. The reports also concluded that the foreigners held 80%–90% of patents and were exploiting the system to achieve monopolistic control of the market (Ramanna, 2002).

workers, culminating in the increase in overall demand for them.[15] Lastly, in column (10) we use average skilled workers' compensation (total skilled workers' compensation/number of skilled workers) as the outcome of interest. We find that the 2002 act increased the average compensation of a skilled worker by about 10% in the highly patentable industries.[16]

Our empirical and conceptual exposition so far indicates that the positive impact of the 2002 act on relative demand for skilled workers is driven only by highly patentable industries. We examine the components of skilled workers' compensation to better understand the sources of the change. We disaggregated compensation into wages and incentives (Table 3).

Table 3: Intellectual Property Rights Reform and Demand for Skilled Workers: Disaggregated into Wages and Incentives

	Skilled Workers' Wages/ Total Wages		**Skilled Workers' Bonuses/ Total Bonuses**	
	(1)	(2)	(3)	(4)
$PatentAct_{2002} \times HPI_j$	0.006***	0.006***	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.242***	0.242***	0.209***	0.210***
	(0.010)	(0.010)	(0.013)	(0.013)
R-square	0.122	0.122	0.042	0.042
N	289,723	289,723	224,446	224,446
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE(4-digit) X Year Trend	No	Yes	No	Yes

Notes:

1. Columns (1)–(2) use share of skilled workers' wages in total labour wages, and columns (3)–(4) share of skilled workers' bonuses in total labour bonuses of a firm as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013).
3. $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
4. Numbers in parentheses are robust clustered standard errors at the industry level.
5. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

[15] Garicano (2000) argued that managerial skill is important for non-routine tasks in production processes.

[16] Table B.2 (Appendix B) does a robustness check for our benchmark results using the ratio of the average wage of skilled workers to that of unskilled workers as the dependent variable. Our estimates continue to show that the 2002 act led to a significant increase in the average wage of skilled workers, to the tune of 2.3%–8.0%.

Columns (1) and (2) examine skilled workers' share of total wages, whilst columns (3) and (4) use skilled workers' share of total bonuses as the outcome of interest in equation (1). The coefficient of the interaction term is positive and significant for wages and has no effect on bonuses. Therefore, differences between highly and less patentable industries in demand for skilled workers is due only to the difference in their share of wages or the fixed component of total compensation.

We perform a set of similar exercises for unskilled workers (**Table 4**). Columns (1) and (2) use the share of unskilled workers' compensation, columns (3) and (4) number of unskilled workers, and columns (5) and (6) average unskilled workers' compensation. We find that $PatentAct_{2002}$ negatively affects unskilled workers across all dimensions. It significantly reduces the share and number of and average demand for unskilled workers. The 2002 act led to greater reduction of employment of unskilled workers by about 4.5%–8.0% in highly patentable than in less patentable industries. The negative effect on average unskilled workers' compensation is about 1.2%–1.8%. These results show strong evidence that capital–skill complementarity might be at play.

Combining all the results, we can possibly infer that that the 2002 IPR reform might have significantly contributed to wage inequality between skilled and unskilled workers. This is because, firstly, it increased skilled workers' value more for highly patentable than for less patentable industries. Secondly, the same reform led to a decrease in unskilled workers' employment and share of compensation. In a similar context, Vashisht (2017) found that adoption of new technology increased the demand for high-skill workers at the cost of intermediary skills, leading to the polarisation of manufacturing jobs. These results suggest that technology has reduced routine tasks in manufacturing jobs.[17]

[17] Table B.3 (Appendix B) does a robustness check for our benchmark results using the 1999 act. Columns (1)–(4) use share of skilled workers' compensation, columns (5)–(6) share of skilled workers' wages, and columns (7)–(8) share of skilled workers' bonuses as the dependent variable, respectively. The results show that the 1999 act led to significant increase in compensation share of skilled workers and that the increase in compensation was driven by the increase in wages.

Table 4: Intellectual Property Rights Reform and Demand for Unskilled Workers

	Unskilled Workers' Compensation/Total Compensation		Number of Unskilled Workers		Average Compensation (Unskilled)	
	(1)	(2)	(3)	(4)	(5)	(6)
$PatentAct_{2002} \times HPI_j$	-0.022***	-0.015***	-0.045***	-0.078***	-0.012**	-0.018***
	(0.004)	(0.004)	(0.013)	(0.013)	(0.005)	(0.005)
Constant	-0.577***	-0.590***	4.202***	4.263***	10.31***	10.32***
	(0.026)	(0.026)	(0.083)	(0.034)	(0.035)	(0.035)
R-square	0.126	0.126	0.165	0.165	0.258	0.258
N	338,499	338,499	338,441	338,441	338,367	338,367
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE(4-digit) X Year Trend	No	Yes	No	Yes	No	Yes

Notes:

1. Columns (1)–(2) use share of unskilled workers in total compensation, columns (3)–(4) total number of unskilled workers, and columns (5)–(6) average compensation of unskilled workers.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013).
3. $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
4. Numbers in parentheses are robust clustered standard errors at the industry level.
5. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

4. 3. Complementary Effects

By using several controls in Table 5, this section controls for other possible channels that might simultaneously affect a firm's skilled workers' compensation. Whilst some of these channels do have significant effects, our primary result remains true and significant in every case, establishing that IPR reforms indeed contributed to higher relative demand for skilled workers in highly patentable industries.

Table 5: Intellectual Property Rights Reform and Demand for Skilled Workers: Controlling for Other Possible Channels

	Skilled Workers' Compensation/Total Compensation				
	Domestic Market Competition – China	**Export Market Competition – China**	**Management Technology**	**Factories**	**Computer Use Fees**
	(1)	(2)	(3)	(4)	(5)
$PatentAct_{2002} \times HPI_j$	0.008*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.009*** (0.002)	0.004+ (0.002)
$DComp_{IN}^{China} \times HPI_j$	-0.0002** (8.13e-05)				
$FComp_{IN}^{China} \times HPI_j$		3.17e-05 (9.86e-05)			
$ManTech_j \times HPI_j$			0.041*** (0.005)		
$Factories_{j,t-1} \times HPI_j$				1.36e-05** (5.68e-06)	
$ITFees_{j,t-1} \times HPI_j$					0.008*** (0.004)
Constant	0.242*** (0.010)	0.242*** (0.010)	0.242*** (0.010)	0.242*** (0.010)	0.242*** (0.010)
R-Square	0.128	0.128	0.122	0.122	0.123
N	270,774	269,161	289,723	289,723	289,723
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE(4-digit) X Year Trend	Yes	Yes	Yes	Yes	Yes

Notes:

1. Columns (1)–(5) use share of skilled workers' compensation in total labour compensation of a firm as the dependent variable.
2. $DComp_{IN}^{China}$ is the measure of competition from imports from China faced by domestic firms. $FComp_{IN}^{China}$ is the measure of export market competition faced by Indian firms in an export destination (United States). $ManTech_j$ is an index of management quality at the 2004 NIC 2-digit level (sourced from Bloom and Van Reenen [2010]). $Factories_{j,t-1}$ is the number of factories at the 3-digit level NIC 2004. $ITFees_{j,t-1}$ is the expenditure by a firm for information technology–enabled services. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
3. Numbers in parentheses are robust clustered standard errors at the industry level.
4. +Standard at the 12% level, *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

4.3.1. Trade Shocks

We start by controlling for other possible trade channels that might concurrently affect skilled workers' compensation in columns (1) and (2). Caliendo and Rossi-Hansberg (2012) pointed out that trade significantly affects the organisational structure of firms through increase in demand for managers (Cunat and Guadalupe, 2009; Chakraborty and Raveh, 2018). Chakraborty and Raveh (2018) used the trade liberalisation exercise adopted by India during the 1990s to examine its effect on demand for managers, and showed that drop in input and not output tariffs significantly explains the rise in the share of managerial compensation for manufacturing firms. Cunat and Guadalupe (2009) and Guadalupe and Wulf (2010) showed that import and product market competition significantly affected managerial or executive compensation. We use Chinese competition as a proxy for import competition.[18]

We follow Chakraborty and Henry (2019) and used China's entry to the WTO in 2001 as a quasi-natural experiment for the possible indicator for import competition from China in column (1) to measure such effect.[19] Our variable of interest was $DComp_{IN}^{China} \times HPI_j$. $DComp_{IN}^{China}$ is a measure of competition from China that an industry faced because of China's unilateral liberalisation policies. It is the share of imports from China in total imports by industry j. We use lagged value of the share of imports from China at the 2004 NIC 4-digit level. Therefore, $DComp_{IN}^{China}$ provided a measure of the amount of competition faced by Indian firms in the domestic market because of China becoming a WTO member. The interaction term provides a clear and exogenous measure of import competition from China. To measure the differential effect of import competition from China on skilled workers' compensation, we interact $DComp_{IN}^{China}$ with our HPI_j dummy. We find a tiny effect of domestic competition from imports from China.

[18] India's imports from China increased from about 1% in 1992 to 17% in 2006; the increase in the share was especially sharp in 2001–2006, from 5.5% to 17.0%.

[19] The ASI does not give any information on trade by the plants. To overcome such a shortcoming, we match the plant-level data from the ASI with the trade destination–based product-level UN-COMTRADE dataset at the NIC 2004 4-digit level.

Caliendo et al. (2017) argues that participation in export markets can significantly increase managerial compensation. In column (2), we use the share of imports from China in total imports of the US to see whether export market competition, $FComp_{IN}^{China}$, positively affected the share of skilled workers' compensation. We find no effect of export market competition on skilled workers' compensation.

4.3.2. Other Possible Channels

We follow Chakraborty and Raveh (2018) and test for other industry- and firm-level channels in columns (3)–(5). We start by testing the potential correlation between skilled workers' compensation and management technology. We use data on management technology from the World Management Survey in column (3). Data are given only for 2004 across all NIC 2004 2-digit industries. To measure the effect of management technology, we interacted the index with the HPI_j. Our estimate points out that there is an interaction effect of management technology and IP intensity of industries. Compensation of skilled workers increased by 4.1% in highly patentable industries where management technology was high. In other words, the higher the management technology, the higher the difference in demand for skilled workers between highly and less patentable industries. Our main variable of interest is still positive and significant.

Establishment of new factories might create demand for new skilled workers, as local knowledge is important (Bloom et al., 2010). Therefore, we used an additional related measure: the number of factories and plants at the industry level in column (4). The inclusion of this additional control did little to change our benchmark finding. We find infinitesimal effect (positive) of new factories on skilled workers' compensation.

The sudden expansion in information technology services in the early 2000s, which we ascribe to IPR reforms, might explain some of the increased relative demand for skilled workers in highly patentable industries. To control for this, we used expenditure incurred by firms for use of computers in column (5). We find a significant effect of the greater use of computers on the share of skilled workers' compensation. Skilled workers in highly patentable industries experienced a 0.8%

increase in their compensation due to increased use of computer-related services. However, the sign and significance of our main channel does not go away.

4.4 Plant and Industry Characteristics

We now examine the heterogeneity of our results in **Table 6,** using a key plant and industry characteristic to identify the set of plants and/or industries that drives the main results. We present our results only for the 2002 act.[20] We start by dividing the plants into four quartiles corresponding to total output of the industry to which the plants belonged. For example, if the total output of a plant was below the 25th percentile of total output of the corresponding industry, then that plant industry belonged to the first quartile. The variable would indicate 1 for that plant and 0 otherwise. If a plant's total output lay between the 25th and 50th percentiles of total output, the plant was in the second quartile; if between the 50th and 75th percentiles, the third quartile; and if above the 75th percentile, the fourth quartile. We find that our aggregate result is driven by big plants or plants above the 75th percentile.

Lastly, in columns (5) and (6) we follow Nouroz (2001) and used the input–output classifications to categorise firms by end use of their products: intermediate (intermediate, basic, and capital) and final (consumer durable and non-durable) goods. The interaction effect is significant only for industries producing intermediate products.

[20] Results are similar for the 1999 act.

Table 6: Intellectual Property Rights Reform and Demand for Skilled Workers: Size Classifications and End-use Categories

	Skilled Workers' Compensation/Total Compensation					
	Size Classifications				End Use	
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	Final Goods	Intermediate Goods
	(1)	(2)	(3)	(4)	(5)	(6)
$PatentAct_{2002} \times HPI_j$	0.003	0.004	0.004	0.006**	0.003	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.281***	0.263***	0.226***	0.210***	0.239***	0.257***
	(0.033)	(0.022)	(0.019)	(0.014)	(0.009)	(0.005)
R-Square	0.138	0.111	0.143	0.168	0.107	0.062
N	72,181	72,180	72,180	72,180	140,096	120,175
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE(4-digit) X Year Trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes:
1. Columns (1)–(6) use share of skilled workers' compensation in total labour compensation of a firm as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
3. Plants are classified into quartiles according to total capital employed. If a plant's total capital employed is below the 25th percentile of total capital employed of an industry, the plant is placed in the 1st quartile, and so on.
4. Columns (5) and (6) classify industries according to their end use; column (5) combines consumer durable and consumer non-durable goods into final goods industries; and column (6) combines basic, intermediate, and capital goods industries into intermediate goods industries.
5. Numbers in parentheses are robust clustered standard errors at the industry level.
6. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

4.5. Other Effects

To explain the other effects of the patent reforms, we discuss the effect of IP law on three industry-level issues: productive factors, product variety, and effect on patenting activity (Table 7).

Since, the ASI does not provide information on technology use or product variety, we match the ASI dataset with PROWESS[21] at the industry level to bring forth such information and explore other crucial effects of IPR. Columns (1)–(3) show significant evidence of the effect of the 2002 IPR act on productive factors in terms of R&D expenditure, transfer of technology (we use royalties for technical know-how as an indicator), and capital employed. Highly patentable industries spend significantly more on R&D and technology transfer and employ more capital because of the change in IP law. The reallocation of productive factors across firms points to a capital–skill complementarity channel that might be at work. Our estimates show that the 2002 IPR reform led to about a 64% increase in R&D expenditure for highly patentable industries, 20% increase in technology transfer, and 25% increase in capital employed.

We estimate the effect of the change in the IP law on product scope or the number of product varieties produced by an industry. The implementation of the law on product patent filings should have had a positive effect on the number of product varieties produced, especially for highly patentable industries. Column (4) shows that the change in the IP law resulted in highly patentable industries producing about 3% more number of products than less patentable industries did.

[21] PROWESS is a dataset of manufacturing firms, constructed by the Centre for Monitoring the Indian Economy. The dataset was used by Khandelwal and Topalova (2011), Ahsan and Mitra (2014), and Chakraborty and Raveh (2018), amongst others. The dataset accounts for more than 70% of economic activity in the organised industrial sector, and 75% of corporate and 95% of excise duty taxes collected by the government (Goldberg et al., 2010). The database contains information on 27,400 publicly listed companies, all within the organised sector, of which almost 11,500 were in manufacturing. Whilst classified according to the 4-digit 2008 NIC level, firms were reclassified to the 2004 level to facilitate matching with the ASI dataset. PROWESS reports direct measures on a vast array of firm-level characteristics, including R&D expenditures, technology transfer, capital employed, and others. The dataset covers large and small enterprises.

Table 7: Intellectual Property Rights Reform and Demand for Skilled Workers: Other Effects

	Factors of Production			**Product Characteristics**	**Patent Claims**
	R&D Expenditure	**Technology Transfer**	**Capital Employed**	**Scope**	**Product Claims/Total Claims**
	(1)	(2)	(3)	(4)	(5)
$PatentAct_{2002} \times HPI_j$	0.644^{***}	0.198^{***}	0.249^{***}	0.028^{***}	0.434^{***}
	(0.028)	(0.027)	(0.013)	(0.010)	(0.163)
R-Square	0.741	0.684	0.950	0.853	n/a
N	1,581	1,580	1,462	1,197	754
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE(4-digit) X Year Trend	Yes	Yes	Yes	Yes	Yes

R&D = research and development.

Notes:

1. Column (1) uses R&D expenditure, column (2) expenditure on technology transfer, column (3) capital expenditure, and column (4) product variety of an industry as the dependent variable. In column (5), we use share of product claims in total patent claims of an industry as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
3. Numbers in parentheses are robust clustered standard errors at the industry level.
4. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

Lastly, we show whether the 2002 act had any effect on a firm's patenting activity. The period between the imposition of the 2002 act and the end of our sample period is not long enough (just 5 years) to understand whether IPR reform led to an increase in product patents earned by a firm. As a proxy, we look at whether the 2002 act induced firms to file for more product patent claims after 2002.

We utilise data from patent filings by manufacturing firms with the Indian Patent Office (IPO). Firm innovative activity data came from the EKASWA database assembled by the Patent Facilitating Centre of the Department of Science and Technology. EKASWA contains all domestic patents published from January 1994 to early 2011. We restrict the data until 2007. Our analysis focuses on the share of total product claims in total number of patent claims by an industry at the NIC 4-digit level. Due to the absence of a unique identifier between the firm-level balance sheet and firm-level patent data, the main problem in matching these two datasets was in matching assignee names in the patents to firm names.

To match assignee names to firm names, we rely on a simple combination of an automated matching algorithm and an extensive manual checking of the (un)matched data. We match about 30%–35% of patent data to the industry-level data. Therefore, the results we present here might be a lower bound of the true effects of the 2002 act on claims of product patents filed.

Column (5) uses share of product claims in total patent claims filed by a manufacturing industry with the IPO. Because of the prevalence of a high proportion of zeros in the dependent variable, we used binomial regression. Our variables of interest, $PatentAct_{2002} \times HPI_j$, are positive and significant, meaning that highly patentable industries had more product claims in their patent filings than less patentable industries after 2002. An average highly patentable industry filed for 54% more product claims after 2002 than an average less patentable industry. We find that strengthening patent law induced highly patentable industries to adopt more technology, produce more products, and file for more patents.

5. Concluding Remarks

The change in the IPR regime, as encapsulated by the implementation of the 2002 act, had the following effects. IPR reform led to a significant increase, statistically and economically, in demand for skilled workers across intensive (compensation as a share of total labour compensation) and extensive (employment as a share of total employment) margins. The increase in relative value of skilled workers was significantly more (0.5%–2.9%) for highly patentable industries. The effect was consistently significant across various specifications. By disaggregating total skilled workers' compensation into wages and incentives, we found that it was the share of wages rather than incentives that explained the difference between highly and less patentable industries.

These effects were driven by big plants and plants belonging to industries producing intermediate inputs. We find that IPR reforms led to increased technology adoption and capital employed. Highly patentable industries, because of the change in the IPR laws, started to produce more product varieties and filed for more product patent claims. These results hint at a possible quality-upgrading mechanism.

Acemoglu and co-authors showed that skill was more valuable to firms closer to the technological frontier, particularly firms engaged more in innovation than imitation (Acemoglu et al., 2006; Acemoglu et al., 2007). IPR reforms increased the relative value of product innovation over process imitation by introducing monopoly rights over new products. As a result, there was an economy-wide increase in demand for skilled workers.

Our results showing increase in technology adoption and innovation capabilities as a complement to skilled workers' inputs are consistent with the idea of a firm as a problem-solving entity (Garicano, 2000). The production process involves workers solving a flow of problems. Unsolved problems travel up organisational layers and a manager's or skilled worker's role is to attend to the exceptional problems occurring within his or her span of control. The organisational hierarchy is designed to optimise skilled workers' or managers' time and maximise problem-solving efficiency. The IPR reforms increased the value of new products, and as a firm developed more new products, the complexity of problems faced by the firm increased significantly. Since unskilled or production workers (non-managers) faced more challenging or exceptional problems, the role of a skilled worker became more valuable to firms. This explains the increase in demand for skilled workers relative to non-skilled workers consequent to the IPR reform.

Our results are indicative of the kind of changes a developing economy such as India goes through with increasing formalisation and integration with the global economy. Given that the TRIPs+ provisions are soon to be implemented in the least developed countries, our results might have implications across these newly IP-acceding nations, such as the observed wage inequality between skilled and non-skilled workers as well as between highly and less patentable industries. Such wage polarisation (Cozzi and Impullitti, 2016) appears to be an important economic trade-off associated with globalisation of developing economies. Our case presents an opportunity to more carefully examine the effects of IPR on wage inequality across nations such as Brazil, Chile, China, and others, using employer–employee datasets to extend our work, bringing in more evidence on the welfare effects of IPR across the world.

We close this section with a comparison of IPR shock and trade shock. Some of our results, such as increased demand for skilled workers, higher between-industry wage inequality, and others, have been observed elsewhere due to increased competitiveness because of trade shocks. However, whilst a trade shock typically affects industries engaged in export or import, we found that a change in property rights over innovation affects virtually all economic sectors. It is this pervasive impact that underlines the importance of IP as a lever of market power, policy, and driver of welfare.

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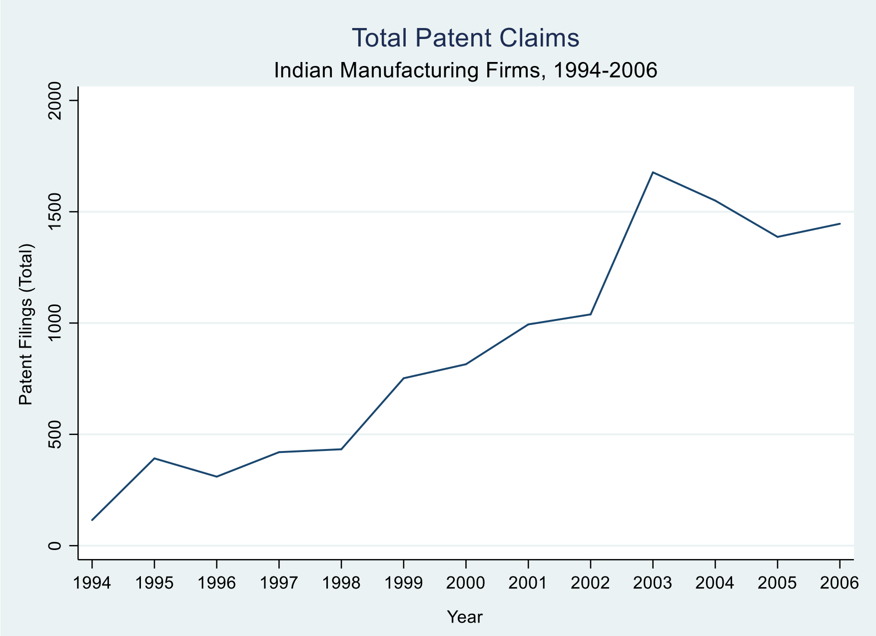
Appendix

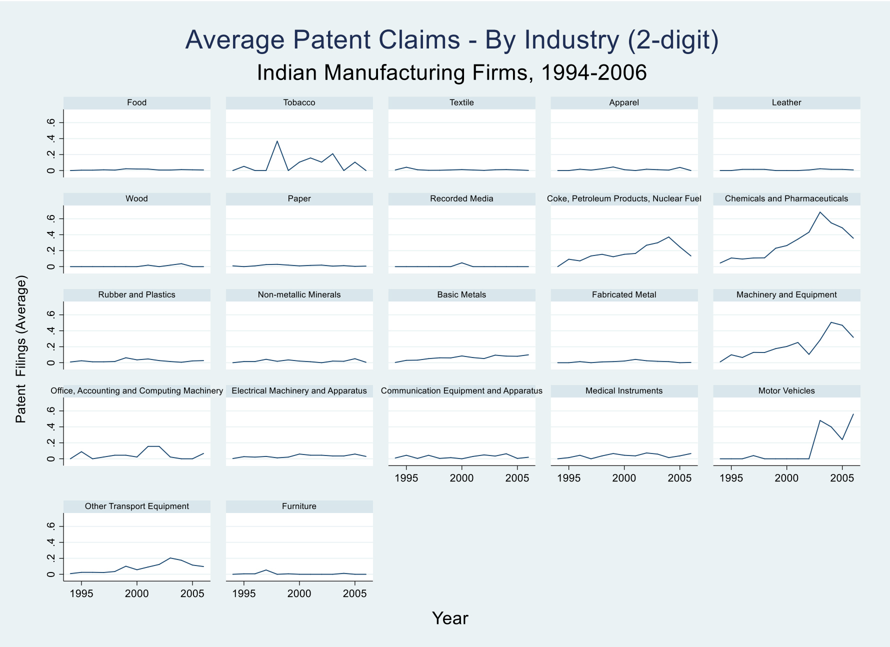
A. Figures

Figure A.1: Total Patent Claims: Indian Manufacturing Firms, 1994–2006



Notes: Figure presents the total patent claims across all manufacturing firms in India, 1994–2006.
Source: Authors.

Figure A.2: Average Patent Claims: By Industry (2-digit), 1994–2006



Notes: Figure presents the average patent claims by industries (2-digit), 1994–2006.
Source: Authors.

B. Tables

Table B.1: Patents Claims Filed at 2-Digit NIC Industry Level

NIC 2004	Industry Name	Total Patents Filed	Product Patents Filed	Process Patents Filed	Patent Claim Possibility (%)
		(1)	(2)	(3)	(4)
22	Publishing, Printing and Reproduction of Recorded Media	4	2	2	0.37
20	Wood and Wood Products	5	3	2	0.57
36	Furniture and Misc. Manufacturing	14	14	0	0.64
19	Tanning and Dressing of Leather	14	10	4	0.87
16	Tobacco Products	21	13	8	8.50
30	Office, Accounting and Computing Machinery	27	26	1	4.79
18	Wearing Apparel	29	24	5	1.34
34	Motor Vehicles, Trailers and Semi-trailers	50	39	11	13.23
28	Fabricated Metal Products	45	41	4	1.22
21	Paper and Paper Products	52	40	12	1.27
32	Radio, TV and Communication Equipment and Apparatus	68	56	12	2.46
33	Medical, Precision and Optical Instruments, Watches and Clocks	54	52	2	3.76
26	Other Non-metallic Mineral Products	108	44	64	1.93
17	Textiles	142	100	42	0.98
31	Electrical Machinery and Apparatus	139	117	22	3.23
15	Food Products and Beverages	176	94	82	0.99
25	Rubber and Plastics Products	183	143	40	2.40
23	Coke, Refined Petroleum Products and Nuclear Fuel	248	120	128	17.05
35	Other Transport Equipment	526	474	52	8.28
27	Basic Metals	809	474	335	6.11
29	Machinery and Equipment	1837	1339	498	21.12
24	Chemicals and Pharmaceuticals	7099	3712	3387	29.32

NIC = National Industrial Classification.
Note: Numbers in columns (1)–(3) are the sums of all patents filed, and column (4) is the average probability of patent claim by a manufacturing firm belonging to these industries in 1994–2006 at 2-digit NIC 2004.
Source: Authors.

Table B.2: Intellectual Property Rights Reform and Demand for Skilled Workers: Using the Ratio of Average Wage of Skilled Workers to Unskilled Workers as the Dependent Variable

	Average Wage of (Skilled Workers/Unskilled Workers)			
				ATE
	(1)	(2)	(3)	(4)
$PatentAct_{2002} \times HPI_j$	0.054***	0.023***	0.048***	0.079***
	(0.006)	(0.006)	(0.014)	(0.003)
Constant	1.002***	1.057***	1.054***	1.017***
	(0.041)	(0.040)	(0.041)	(0.041)
R-square	0.065	0.066	0.076	0.075
N	286,043	286,043	286,043	286,043
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HPI_j X Year FE	No	No	Yes	No
Industry FE(4-digit) X Year Trend	Yes	Yes	Yes	Yes

Notes:

1. Columns (1)–(4) use the ratio of the average share of skilled workers' compensation to unskilled workers' labour compensation of a plant as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{2002}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 2002, and 0 otherwise.
3. Numbers in parentheses are robust clustered standard errors at the industry level.
4. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

Table B.3: Intellectual Property Rights Reform and Demand for Skilled Workers: Using the Patent (Amendment Act), 1999

	Skilled Workers' Compensation/ Total Compensation				Skilled Workers' Wages/ Total Wages		Skilled Workers' Bonuses/ Total Bonuses	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PatentAct_{1999} \times HPI_j$	0.005*	0.005*	0.029***	0.026***	0.005*	0.005*	0.003	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.241***	0.242***	0.197***	0.201***	0.242***	0.242***	0.209***	0.211***
	(0.010)	(0.010)	(0.030)	(0.020)	(0.010)	(0.010)	(0.013)	(0.009)
R-square	0.122	0.122	0.076	0.076	0.122	0.122	0.042	0.042
N	289,723	289,723	289,723	289,723	289,723	289,723	224,446	224,446
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE X $PatentAct_{1999}$	No	No	Yes	No	No	No	No	No
Industry Output X $PatentAct_{1999}$	No	No	No	Yes	No	No	No	No
Industry FE(4-digit) X Year Trend	No	Yes	Yes	Yes	No	Yes	No	Yes

Notes:

1. Columns (1)–(4) use share of skilled workers' compensation in total compensation, columns (5)–(6) skilled workers' wages in total wages, columns (7)–(8) skilled workers' bonuses as a share of total labour bonus of a plant as the dependent variable.
2. HPI_j is a dummy variable, which takes a value 1 if an industry belongs to the highly patentable group (Delgado et al., 2013). $PatentAct_{1999}$ is a year dummy variable, which takes a value 1 if year is greater than or equal to 1999, and 0 otherwise.
3. Numbers in parentheses are robust clustered standard errors at the industry level.
4. *Standard at the 10% level, **Standard at the 5% level, ***Standard at the 1% level.

Source: Authors.

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