ISSN No. 2454 - 1427

CDE
January 2026

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Working Paper No. 360

Centre for Development Economics
Delhi School of Economics
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Intellectual Property Rights Enforcement and Industry Dynamics: Evidence from Indian Panel Data

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Abstract

This paper examines the impact of the strengthening of intellectual property rights (IPR) on industry-level outcomes such as sales, innovation, and profitability in India, for the period 1990-2020. We first construct a novel industry-specific IPR implementation index that reflects *de facto* enforcement across 27 two-digit industries. Industry outcomes are then modelled using industry data at the two-digit level. The empirical results reveal significant heterogeneity in the effects of IPR regimes. Stronger IPR protection disproportionately benefits firms with higher R&D intensity, amplifying both R&D investment and profitability, with robustness checks confirming consistency across alternative specifications. However, the gains from IPR protection are less pronounced for firms heavily engaged in innovation. This interaction may also reflect a strategic shift in firm behavior rather than a decline in performance. IPR reform positively affect R&D and profitability, particularly in pharmaceuticals and advanced manufacturing. The strengthening of IPR is a powerful driver of performance when paired with internal innovation capacity, highlighting the critical role of absorptive capacity.

JEL Code: O34, C43, K11, L16
Keywords: Intellectual property rights, enforcement, de facto index, industry

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1. Introduction

Strengthening IPR plays an important role in shaping industry-level dynamics, influencing firms' strategic behavior, innovation incentives, and competitive positioning. Stronger IPR regimes can encourage firms to invest more in research and development by enhancing the expected returns on innovation and reducing the risks of imitation (Hall and Ziedonis, 2001; Arora et al., 2001). This is particularly relevant in technology-intensive sectors where appropriability conditions are critical for justifying innovation-related expenditures. At the same time, robust IP protection can alter market structure by reinforcing the dominance of firms with larger patent portfolios, potentially affecting entry dynamics and industry concentration (Lanjouw and Schankerman, 2004; Lerner, 2009). Thus, the degree of IPR enforcement is not merely a legal matter, but a key driver of industrial organization and sectoral growth.

Although industries differ in their need for intellectual property protection (Teece, 1986; Levin et al., 1987; Cohen et al., 2000; Cho et. al., 2015), it is more practical and administratively efficient to adopt a uniform IPR framework across all sectors. Designing distinct laws for each industry would be both unmanageable and unsustainable, especially given that sectoral boundaries are fluid and continuously shifting with technological progress. For example, while pharmaceuticals and software have long been IPR-intensive, sectors like agriculture or construction may increasingly require IP protection as they modernize (Lanjouw and Schankerman, 2001). A standardized legal framework provides legal certainty while allowing flexibility in how laws are enforced or interpreted across contexts (Correa, 2000; Maskus, 2000). However, despite aiming for harmonization, the TRIPS agreement disproportionately affects manufacturing and patent-intensive industries (Maskus, 2000; Lall, 2003).

Even with uniform statutes, implementation of these laws often varies across industries due to judicial discretion, as courts may interpret or prioritize cases differently based on sector-specific concerns. Additionally, sector-specific lobbying and the economic relevance of certain industries may lead to a stronger emphasis on enforcing IPR laws in some sectors over others which further creates variation in the actual IP compliance.

Furthermore, while many studies have examined the economic impact of IPR regimes, most rely on cross-country indices such as the Ginarte and Park (1997) patent right index, which has been widely used to assess IPR strength across countries over time. While this index is comprehensive in capturing the legal components of IPR regimes, such as patent duration, enforcement provisions, and international treaties, it does not account for how these laws are applied across different industries in practice. It primarily captures the de jure dimensions of

IPR regimes, but fails to reflect the actual ground-level implementation of laws. Moreover, Ginarte and Park (1997) lack granularity in terms of industry-wise differentiation, thus overlooking intra-national and sectoral variations in enforcement that could be critical for policy and economic outcomes.

This study addresses these gaps by introducing a novel, industry-level de facto IPR implementation index for India. To our knowledge, this is the first effort to construct an IPR index that varies by both industry and time within a single country. By doing so, we aim to capture not only the presence of IPR laws but also their practical application and enforcement across diverse industrial sectors. This distinction is crucial, as theoretical protection does not always translate into effective protection, and the economic impacts of IPRs are likely to depend on the latter.

The objective of this paper is twofold: to empirically analyze the temporal and cross-sectional variation in the implementation of IPRs across Indian industries, and to examine the implications of this variation on key industry-level outcomes such as sales, R&D expenditure, and profitability. Further, we extend our analysis to explore heterogeneity in outcomes across different types of industries, such as high- versus low-R&D intensive sectors, and industries that rely more heavily on specific IP instruments (e.g., patents, copyrights, trademarks) versus those that do not. This multi-dimensional approach offers a more detailed understanding of how IPR enforcement interacts with the structural characteristics of industries.

2. Literature Review

A significant body of research has explored how the strength and enforcement of intellectual property rights (IPRs) influence industry outcomes, especially in developing and emerging economies. These studies generally agree that well-designed IPR regimes can affect innovation incentives, technology transfer, market structure, and firm performance. However, they also highlight that the effect of IPR enforcement is heterogeneous, i.e., varying across countries, sectors, and institutional contexts.

For example, Hall and Ziedonis (2001) analyzed the U.S. semiconductor industry and found that firms increased their patenting activity in response to stronger IPRs, particularly to protect against litigation and to maintain bargaining power in cross-licensing negotiations. Similarly, Branstetter et. al., (2006) showed that IPR reforms in developing countries stimulated foreign direct investment and international technology transfer. In another cross-country study, Lerner (2002) highlighted that the impact of patent protection on innovation depends significantly on the quality of supporting institutions. Falvey, et. al., (2006) also noted that stronger IPRs tend to support economic growth, particularly in countries with effective legal systems and in sectors where imitation risks are high.

While these studies emphasize the importance of IPRs for industrial performance, most rely on country-level indices such as the Ginarte and Park Index (1997) or the International Property Rights Index. These indices primarily reflect de jure legal provisions, such as patent duration, coverage, and enforcement mechanisms but do not measure how IPR laws are actually implemented on the ground, nor do they capture variation across industries within a country.

This limitation is particularly significant in the Indian context, where the post-TRIPS era has seen a phased and evolving approach to IPR legislation. Here, the contributions of Kanwar and Evenson (2009), stand out for their depth and empirical rigor. For example, Kanwar and Evenson (2009), examined the relationship between national IPR strength and R&D investment across developing economies and found a positive correlation but also cautioned that the benefits depend on contextual factors such as legal enforcement and economic capacity. Focusing specifically on India, Kanwar and Sperlich (2020) investigated the impact of IPR reforms on innovation and productivity in Indian manufacturing. Their results suggest that IPR strengthening combined with improved access to foreign technologies, helped push the innovation frontier, especially in more technologically dynamic sectors. This aligns with the broader view that IPR reforms alone are not sufficient unless supported by mechanisms that encourage practical enforcement and absorptive capacity.

Despite these important contributions, much of the existing literature allows for a uniform application of IPR laws across sectors. It does not directly capture de facto implementation, i.e., the actual enforcement of IP rights across different industries. This enforcement can vary significantly even when the statutory laws remain the same, due to factors such as judicial discretion, industry lobbying, administrative capacity, or legal awareness. Moreover, in India, the adoption of IPR laws has occurred in phases through successive amendments, which is not adequately captures by the existing indices. This paper seeks to address this critical gap. By constructing a novel industry-wise de facto IPR implementation index for India based on realized enforcement outcomes such as litigations, registrations, and case resolutions. It shifts the focus from legal formalism to enforcement reality. This new index allows us to observe how IPRs are actually implemented across 33 two-digit industries over time, and to investigate their effects on key outcomes such as industry-level sales, R&D intensity, and profitability.

3. Construction of Industry-Time *De facto* IPR index

This study creates and employs a novel *de facto* IPR Implementation (IPRI) Index reflecting variations in the execution of intellectual property rights laws in India from 1970 to 2020[3] on a quinquennial frequency. To create the IPRI Index, a comprehensive database is compiled from IPR infringement lawsuits heard in Indian courts, including District and High Courts using Indian Kanoon and E-Courts that are reliable Indian websites for judicial cases. This database encompasses various details for each collected lawsuit based on the legal provisions such as the grant and pace of preliminary injunction, burden of proof reversal, other reliefs granted, duration of the suit, origin of plaintiffs and defendants, jurisdiction and related industry of the infringed product or service, settlement issues, and final verdicts which is scored accordingly. The following are the details of the underlying components that were considered in the construction of the index, along with their scoring strategies:

1) <u>Provision of preliminary injunction</u>: An injunction is a preventive remedy granted by the court to stop any wrongful action by the infringing party, preventing further injury to the plaintiff. This remedy is effective not only in intellectual property infringement cases but also in other scenarios, such as restraining a defendant from using a plaintiff's license without permission *(A.P. State Electricity Board v. Mateti S.V.S. Ramachandra Rao, 2015)*, or from making misleading advertisements that slander a plaintiff's product *(Havells India Ltd. v. Eveready Industries India Ltd., 2015)*. Article 50 of the TRIPS agreement empowers the Indian judicial system to grant preliminary injunctions in IPR infringement cases (Verma, 2004). This enforcement mechanism is significant from both traditional and efficiency viewpoints (Ginarte and Park, 1997; Brooks and Schwartz, 2005). Traditionally, it acts as a barrier to infringement, maintaining the status quo between parties during the lawsuit. From an efficiency perspective, it promotes efficient behavior from the defendant by serving as both a stick (punishment for infringement) and a carrot (reimbursement of compliance costs if the defendant prevails. The score for this component is 1 if a preliminary injunction is granted in an IP infringement lawsuit, and 0 otherwise.
2) <u>The pace of delivering a preliminary injunction in infringement cases</u>: This component indicates the time taken (months/years) to grant the preliminary injunction. The score for this component equals 1 if the preliminary injunction relief is obtained within a

[3] The reason for choosing this timeline is because 1970 is the year when the major act in intellectual property rights i.e., the Patent Act of 1970 was enacted. This timeline also includes the year of TRIPS inclusion. Moreover, the data on the legal search engines for IP infringement cases is available from 1970 onwards.

month, 2/3 if the relief is obtained between 1 and 6 months, 1/3 if it takes between 6 months and a year, and 0 if it takes more than a year[4]. The minimum and maximum time periods considered here are based on the fact that it approximately takes a period of 1 week to 1 year to grant a preliminary injunction, and there are a very few cases in which the duration went beyond a year.

3) Conversion of a preliminary injunction: This component tracks rulings where a preliminary injunction is converted into the final adjudication of a lawsuit. As an interim relief, a preliminary injunction can be converted into a permanent injunction (with or without compensation), substituted with monetary compensation, or vacated at the end of the trial. The score for this factor equals 0 if vacated, 1/3 if only compensation is ordered, 2/3 if converted into a permanent injunction without compensation, and 1 if converted into a permanent injunction with compensation.
4) Burden of proof reversal: This component indicates whether the burden of proof has been shifted on to the defendant, making the court procedure for the plaintiff less burdensome, and supporting litigation in process patent-related issues only. This component is considered only in the patent implementation index[5]. It takes a value of 1 if the burden of proof is on the defendant to prove non-infringement, and 0 otherwise.
5) Anton Pillar orders: The Anton Pillar order is a remedy which allows a search of the defendant's premises and seizure the evidence of infringement, without prior notice to the defendant. These orders are relevant for preserving evidence of intellectual property infringement (Ng, 1997). The order was named after an English case *Anton Piller KG v Manufacturing Processes Limited (1975)*. The score for this component equals 1 if the court orders search and seizure for the discovery of evidence of infringement, and 0 otherwise.
6) Cost entitlement: The relief of 'cost entitlement' is granted by the court to reimburse the cost of the suit (court fee, attorney's fee, and any local commissioner's fee) to the plaintiff, at the end of the suit. If the cost is reimbursed the score equals 1, and is 0 otherwise.
7) Duration of entire lawsuit: This component indicates the *total* length of the patent infringement trial in the Indian courts, right from the date of filing the suit till its final

[4] The variable is negatively skewed, and the data is concentrated between 0.5 and 1, with very little to the left of 0, which means that the time taken to grant the preliminary injunction is beyond 1 year in very few cases.

[5] The provision 'burden of proof reversal' is available in patent infringement cases only according to the Indian Patent Act (1970). In trademark or copyright infringement, there is no such provision available under the Indian Trademark Act (1999) or Copyright Act (1956).

disposal. A greater length, ceteris paribus, is taken to mean a delay in justice, which implies inefficient enforcement of patent infringement cases, whereas a shorter duration is equated with better enforcement. We realize that this supposition is somewhat simplistic, because a longer duration for some cases may have to do with those lawsuits being more complicated rather than having been inefficiently enforced. However, it is not possible to differentiate between more and less difficult cases at present, and therefore we ignore this issue on pragmatic grounds. We estimate the duration score (DS) as:

$$Duration\ Score = 1 - \frac{Number\ of\ years\ spent\ in\ resolving\ the\ dispute}{20} \quad [1]$$

Thus, its value ranges from 0 to 1, where smaller values indicate weaker enforcement of patent rights and larger value indicate the converse. Hence, an increase (decrease) in the number of years spent in resolving the patent infringement dispute decreases (increases) the score value, implying less (more) efficient enforcement. The denominator (20 years) represents the standard term of patent protection under the TRIPS agreement. If the dispute settlement is delayed beyond 20 years, that amounts to justice denied and 'weak' enforcement (i.e., any negative score is considered equivalent to 0 for simplicity in interpretation[6]).

For convenience, we group all the like factors under the following four broad categories:

(i) Preliminary injunction - measured as the unweighted sum of the scores for provision of a preliminary injunction, pace of grant of a preliminary injunction, and conversion of a preliminary injunction into a permanent injunction, monetary compensation (or both) or vacation.

(ii) Burden of proof reversal - measured as the score relating to shifting the burden of proof from the plaintiff to the defendant;

(iii) Other entitlements - measured as the unweighted sum of the scores of the Anton Pillar and cost entitlement factors, and;

(iv) Duration of the lawsuit - measured as the score pertaining to the length of an IP infringement lawsuit.

[6] We could also estimate DS = (actual yrs – min yrs) / (max yrs – min yrs), where max and min are the max and min of our sample. This could avoid any negative values and the index could also vary between 0 and 1. However, here, we are focused on the moral dimension of the justice delivered, i.e., "justice delayed is justice denied". So, any infringement case taking more than 20 years indicates justice denied, no matter if the case is taking let's say, 21 years or 50 years. Even one year of delay shows that the court has exceeded the threshold of standard patent term to resolve the case which indicates 'weak enforcement' and for weak enforcement, we have given a score of 0.

We also wanted to add the 'cost of litigation' as a fifth category for our proposed index, because it is indicative of the monetary hurdles faced by IP owners during various stages of the trial. Thus, the higher the cost of litigation, the more difficult it is for IP owners to opt for litigation as a way of getting justice from the courts. This constitutes a hurdle in the implementation of the IP laws, and makes the enforcement mechanism relatively less relevant. Thus, a high cost of litigation effectively implies weaker protection than is available on paper. A high cost of litigation pushes parties to opt for alternative dispute resolution remedies, such as out-of-court settlement or mediation (WIPO, 2010)[7], which may yield sub-optimal redressal from the plaintiff's viewpoint. However, due to lack of cost-related information we are not able to include this factor in our proposed index.

To compute our industry and time-varying de facto IPR index, we added the scores of all the four components discussed above (such as preliminary injunction, burden of proof reversal, other entitlement and duration) to find a single score for each of the infringement case in our sample. We then find the simple average[8] of the scores of all infringement cases (whether; patents, copyrights, or trademarks) for each of the 33 two-digit National Industrial Classification (NIC) industries for the period 1970 to 2020[9], irrespective of the type of IP. The rationale for aggregating to the two-digit level is the limited variation over time observed at the more granular three-digit level. We now briefly discuss this methodology for greater clarity.

Step 1: We first compute the preliminary injunction score (PIS_i), burden of proof reversal score ($BPRS_i$), duration of lawsuit score (DL_i), and the other entitlements score (OI_i), for every infringement case i in our sample, where these cases are spread over the sample period 1970 to 2020. How these individual scores are computed has been explained above.

Step 2: Summing the scores of these components PIS_i, $BPRS_i$, DL_i, and OI_i for every infringement case i in our sample, we get X_i. Since the PIS_i score lies between 0 and 3, the $BPRS_i$ lies between 0 and 1, the DL_i lies between 0 and 1, and the OI_i score lies between 0 and

[7] See WIPO Magazine (2010), available at untitled (wipo.int).

[8] We did not use a weighted average because it would not make sense here. Different industries usually rely on one main type of intellectual property. For example, the pharmaceutical industry depends mostly on patents, creative arts rely on copyrights, and apparel or leather industries focus on trademarks. In these cases, almost all infringement disputes in an industry involve just one type of IPR or at most two. So, averaging infringement cases across different IPR types with weights would not reflect the reality of how protection works in each industry.

[9] The averaging of the scores of all the infringement cases belonging to a particular industry and time, makes the dataset a panel data.

2, the measure X_i lies between 0 to 7 for every patent infringement case[10] and 0 to 6 for copyright and trademark infringement cases.

Step 3: For all the infringement cases i in our sample, the total score (X_i) is normalised using the formula[11] $X_i^N = \frac{X_i - Min(X_i)}{Max(X_i) - Min(X_i)}$, so that the normalised sum X_i^N (where superscript N indicates the normalised variable) lies between 0 and 1.

Step 4: Since all the infringement cases i are spread over the sample period of 1970 to 2020 and correspond to different two-digit industries, evidently so is the normalised score X_i^N. The arithmetic mean of X_i^N over all the infringement cases i in a given two-digit industry j for every year t, yields the industry-time IPR implementation index for industry j and year t, i.e., $IPR_{jt} = \underset{i}{Mean}(X_i^N)$ for each industry j and year t, where, j refers to 33 two-digit industries and t = 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020.

4. Dataset and Characteristics

Our dataset[12] comprises a total of 414 intellectual property infringement cases pertaining to patents, copyrights, and trademarks. Out of these 414 cases, 51 or 12.3% relate to patent infringement, 97 or 23.4% relate to copyright infringement, and 266 or 64.3% relate to trademark infringement. Although, patent infringement cases are not large in number, these are the only available infringement cases that were fully disposed-off before our cut-off date of September 2023. Moreover, many cases do not reach the court due to the preference of out-of-court settlement by the parties, because of the high litigation cost. As a result, the sample size of patent cases is small. Out of the available patent infringement cases, the maximum number of cases pertain to the pharmaceutical industry, about 33%, followed by 16% cases from the chemical industry, with the remaining 51% cases belonging to several other industries. Table 1 shows the frequency distribution of patent, copyright, and trademark infringement cases categorized by industry. In this table, we have used the 3-digit level of classification of

[10] This is because the provision of the 'burden of proof reversal' is not available for IP instruments other than patents according to the Indian Patent Act (1970).

[11] The maximum score for the patent cases is 7 and the maximum score for copyright and trademark cases is 6.

[12] For information extraction purposes, we primarily used the 'Indian Kanoon' website, with some material retrieved from the 'Supreme Court Cases' (SCC) website. These are reliable and widely used Indian law search engines, that contain the judgments for cases filed in the Indian courts. Although, the judgments consisted of all the major information that we required, some of the important information such as the date of filing the case, the date of final disposal of the case, and some other details were missing. To collect these details, we had to trace back all the law cases to 'E-Courts' which is an Indian government website that contains information on all State High Courts and District Courts, along with the final judgments.

industries from the National Industrial Classification (NIC 2008)[13], to form groups of small industries such as toothpaste, ties, etc., mentioned in the extracted infringement cases. It shows that around 49% of copyright infringement cases, which is rather high, relate to creative and entertainment industries including artistic works, followed by around 19% cases from the publishing industry, i.e., books, magazines and newspapers, and 15% cases relate to television and broadcasting industries, such as electronic media, TV shows, etc. Further, 50% of trademark infringement cases pertain to pharmaceuticals, food, chemicals, consumer electronics, apparel, and beverages, with the maximum cases relating to the infringement of brand names of pharmaceutical industries. Rest of the 39 industries such as tobacco, footwear, jewellery, bags, etc. shown in the table, relate to the remaining 50% of the infringement cases in trademark. This shows that overall, pharmaceutical, chemical and food industries are more prone to patent and trademark infringement in India, implying that the owners of IP pertaining to these industries are more vulnerable to implementation of IP laws in courts.

Figure 1 presents the trends in the de facto IPR implementation index across a selected group of industries over time. Each subplot corresponds to a two-digit industry and shows the average level of IPR enforcement (solid line), alongside its fitted trend (dashed line), between 1970 and 2020 (with the variation depending on data availability for specific sectors). We find that sectors such as creative, arts and entertainment activities; manufacture of food products such as processing and preserving of dairy, meat, fish and vegetables, manufacture of vegetable oils, etc.; and fabricated metal products show a consistent upward trend in the implementation index over time. This likely reflects gradual institutional strengthening (Maskus, 2000), meaning courts and administrative agencies have become more efficient and consistent in processing IPR-related cases, and increasing legal engagement, which indicates that firms in these industries are more willing to initiate litigation, defend rights, and actively use the legal system to resolve disputes rather than settling informally.

Industries like pharmaceuticals; publishing activities; and computer, electronic and optical products exhibit significant year-to-year fluctuations, indicating that IPR enforcement in these sectors is potentially influenced by sporadic legal events such as the introduction of compulsory licensing in the pharmaceutical sector (e.g., *Natco Pharma Ltd. vs. Bayer Corp.*, 2012, involving a cancer drug patent), high-profile cases such as *Novartis AG vs. Union of India* (2013), which shaped how India treats patentability of incremental innovations, or

[13] See, Ministry of Statistics and Programme Implementation, NIC, 2008 at https://www.ncs.gov.in/Documents/NIC_Sector.pdf

landmark copyright disputes in publishing and software (for e.g., *Penguin Books vs. Rameshwari Photocopy Shop*, 2016). These sectors are more vulnerable to such volatility because they are innovation-intensive, heavily regulated, and frequently subject to international scrutiny, making court rulings and enforcement episodes disproportionately impactful compared to more traditional industries like food processing or metal works.

A few sectors, such as broadcasting and programming activities, and apparel, show either declining or flattening trends in IPR implementation, despite overall increase in national IPR legislation. This suggests either reduced litigation activity, weaker enforcement capacity, or changing industry priorities over time, for example, broadcasting has shifted from analog to digital platforms, where firms increasingly rely on licensing models, content streaming, and digital rights management tools rather than formal court enforcement. In apparel, the rise of fast fashion and global outsourcing has often led firms to prioritize rapid product turnover and branding strategies over litigation-heavy enforcement of design rights.

In many sectors, the de facto implementation does not move in lockstep with expected legal reforms. For instance, even post-TRIPS, industries like Motor Vehicles and Electrical Equipment show relatively modest changes in IPR implementation, underscoring the gap between de jure law (formal adoption of TRIPS-aligned statutes) and actual practice, where firms may either not pursue litigation aggressively or where administrative enforcement remains inconsistent.

These trends reinforce the paper’s central observation that IPR implementation varies significantly across industries, even within a unified legal framework. This justifies the need for a sector-specific IPR implementation index, rather than assuming homogeneous enforcement across the economy. The visual evidence supports the analytical motivation for examining how these differences affect outcomes like R&D, sales, and profitability at the industry level.

5. Methodology

5.1 Conceptual Framework

How does the strengthening of intellectual property rights (IPRs) influence industry-level outcomes in India, specifically sales, R&D investment, and profitability? Evidently, the answer to this question would depend importantly on the index of intellectual property protection that we use. A central innovation of our study is the development and use of a novel, industry-wise de facto IPR index, which measures the actual enforcement of IPRs across different sectors and time periods, as outlined in the above sections. Unlike traditional de jure indices that capture the legal provisions on the statute books, our de facto index reflects the real-world experience of firms and industries with the implementation of the IPR regime by the legal-justice system in our country. This index serves as the key explanatory variable in our empirical analysis, and offers a more precise and context-sensitive measure of IPR protection in India.

The conceptual framework for this study is grounded in three major theoretical perspectives: endogenous growth theory, Schumpeterian innovation theory, and institutional economics. Endogenous growth models emphasize that innovation and knowledge accumulation are internal drivers of long-term economic growth. Stronger IPR regimes are expected to enhance the returns to innovation, thereby encouraging firms to invest more in R&D (Romer, 1990; Aghion and Howitt, 1998). From a Schumpeterian perspective, IPRs grant firms temporary monopoly rights, which can incentivize innovation by ensuring appropriability. However, such monopoly power can also lead to strategic behavior, where firms may reduce output to preserve scarcity and increase prices, potentially resulting in lower sales but higher profits in certain industries (Schumpeter, 1942; Gallini and Scotchmer, 2002). Finally, institutional economics, particularly the work of North (1990), highlights that the effectiveness of institutions, not merely their existence matters for economic outcomes. Hence, the focus on a de facto IPR index aligns with the argument that enforcement and implementation are critical for understanding the real impact of IPR laws.

Within this framework, R&D investment plays a central role. Innovation is theorized to be the most direct and immediate channel affected by IPR strengthening. The assurance of legal protection increases the rewards for innovators and raises the cost for imitators. This directly encourages higher levels of R&D expenditure, which can, in turn, influence both sales and profitability. However, the effect of IPRs on sales and profits may not be uniform across industries. In industries that already invest heavily in R&D, firms may respond to stronger IPR protection by strategically limiting output to increase profitability, exercising the monopoly power granted by patents or copyrights. Thus, innovation itself becomes a moderator in the relationship between IPR and industry performance.

Based on these conceptual models, several hypotheses are developed. First, it is expected that stronger de facto IPR enforcement will positively influence R&D investment. Second, a positive and significant impact is anticipated on industry-level sales and profitability. Third, the interaction between IPR protection and R&D is hypothesized to produce differential effects, especially in industries already engaged in high levels of innovation. For example, while stronger IPRs may encourage further innovation in high R&D sectors, they may also lead firms to leverage their enhanced monopoly rights by raising prices and limiting output, thereby reducing sales but increasing profits. Fourth, the effect of IPR strengthening is expected to vary across different IP-intensive industries and sectoral groupings, reflecting variations in business models, innovation systems, and legal reliance on different forms of IP.

The Indian context of our empirical study provides a unique institutional setting in which to explore these effects. While India has implemented several reforms to align its IPR regime with global standards, actual enforcement remains uneven across sectors. This gap between law and practice makes the use of a de facto index not only novel but necessary for assessing the real impact of IPR on industrial outcomes. Given the heterogeneity of India's industrial base, from informal manufacturing to globally competitive pharmaceutical and IT sectors, understanding the differential effects of IPR policy is both empirically and policy-relevant.

5.2 Theoretical Models for Empirical Estimation

For the sales model, we build upon the standard Cobb-Douglas model following the work of Romer (1986), Lucas (1988), Arellano and Bond (1991), Kim et al. (2012) and Cho et al., (2015). Consider,

$$Y = K^{\alpha_1} Z^{\beta_1} \qquad [2]$$

$$Z^{\beta_1} = H^{\theta} R\&D^{\gamma} IPR^{\delta} \qquad [3]$$

where Y is the sales outcome, K is the physical capital (α is the physical capital elasticity) and Z is the knowledge capital (β is the knowledge capital elasticity) which includes, human capital (H), innovation (R&D) and IPR strengthening (IPR). Substituting (2) in (1) we get:

$$Y = K^{\alpha_1} (H^{\theta} R\&D^{\gamma} IPR^{\delta})^{\beta_1} \qquad [4]$$

$$Y = K^{\alpha_1} H^{\alpha_2} R\&D^{\alpha_3} IPR^{\alpha_4} \qquad [5]$$

Applying logs to equation (4), we get:

$$lnY = \alpha_1 lnK + \alpha_2 lnH + \alpha_3 lnR\&D + \alpha_4 ln(IPR) \qquad [6]$$

Using fixed effects model equation (5) can be written as:

$$lnY_{it} = \alpha_1 lnK_{it} + \alpha_2 lnH_{it} + \alpha_3 lnR\&D_{it} + \alpha_4 lnIPR_{it} + X_{it} + \varphi_i + \omega_t + \epsilon_{it} \qquad [7]$$

X_{it} represents other control variables such as selling and distribution expense, total liabilities, total number of firms, net patent and copyright expense, etc., φ_i and ω_t are industry and year fixed effects and ϵ_{it} is error term.

For the R&D model, we have used the modified version of Sakakibara and Branstetter (2001) model:

$$R\&D = Y^{a} IPR^{b} R\&D_{t-1}^{c} \qquad [8]$$

R&D is the R&D expenditure, IPR represents IPR strengthening, Y is sales, $R\&D_{t-1}$ is last year's R&D expense. Taking logs of equation (7), we get:

$$lnR\&D = alnY + blnIPR + clnR\&D_{t-1} \quad [9]$$

For estimation we have used equation:

$$lnR\&D_{it} = a\ lnY_{it} + b\ lnIPR_{it} + c\ lnR\&D_{it-1} + X_{it} + \varphi_i + \omega_t + \epsilon_{it} \quad [10]$$

X_{it} represents other control variables such as total liabilities, total number of firms, net patent and copyright expenses, etc. φ_i and ω_t are industry and time fixed effects and ϵ_{it} is the error term.

For the profit model, we have used the following model based on the sales model used above:

$$ln\Pi_{it} = \alpha_1 lnK_{it} + \alpha_2 lnH_{it} + \alpha_3 lnR_{it} + \alpha_4 lnIPR_{it} + X_{it} + \varphi_i + \omega_t + \epsilon_{it} \quad [11]$$

Here, Π represents average profits indicated by profit after tax or returns on assets, X_{it} represents other control variables such as Hirschman and Herfindahl (HHI) index, total liabilities, selling and distribution expense, net patent and copyright expense, total firms, etc. φ_i and ω_t are the industry and time fixed effects and ϵ_{it} is the error term.

6. Estimation Data

This study utilizes firm-level data extracted from the Prowess database, Centre for Monitoring Indian Economy (CMIE, 2025), covering the period[14] 1990 to 2020 at five-year intervals.

To facilitate industry-level analysis, we aggregated the firm-level data at the two-digit industry level using the NIC (2008) classification system. The process involved matching more detailed 3-, 4-, and 5-digit NIC codes from the Prowess dataset to their corresponding two-digit industry categories. This concordance was achieved by using a NIC crosswalk table, which included a column explicitly mapping narrower industry codes to their broader two-digit classifications. The crosswalk was merged with the Prowess dataset to create a unified structure for industry-level aggregation. In approximately 135 cases, a direct match was not found, necessitating manual assignment of appropriate two-digit industry codes to ensure completeness and consistency. The following key variables were derived from Prowess database for our empirical analysis:

1. Total Sales (of products and services): total revenue earned from the sale of goods and services, net of excise tax/GST Goods and Service Tax, sales returns, discounts, and inter-divisional transfers.

[14] Although the initial intent was to include data from 1970 onward, however, Prowess records are only available starting in 1990, which constrained the temporal scope of the analysis.

2. Staff Welfare and Training Expenses: Aggregates expenditures on staff welfare (e.g., subsidized healthcare, transport, food, recreation) and training programs for employees. This indicates staff's salary in kind and expenditure to improve skills.
3. R&D Expenditure: or total spending on research and innovation, including salaries for R&D personnel, testing/laboratory costs, and technological development activities. This is an indicator of industry innovation.
4. Selling and Distribution Expenses**:** costs incurred in promoting and delivering products/services, such as advertising, marketing, freight, trade promotion, commissions, and distribution network maintenance.
5. Profit After Tax (PAT): or net income after tax and all revenue expenses, computed as: *PAT = Total Income + Change in Stocks*[15] *(inventories) − Total Expenses*.
6. Return on Assets (ROA): is a profitability ratio measuring how effectively a company utilizes its assets to generate profit, and is calculated as: *ROA = Net Profit / Average Total Assets.* CMIE may also report ROA on a pre-tax basis.
7. Net Tangible Assets: the depreciated book value of fixed tangible assets such as land, buildings, machinery, and vehicles: *Net PPE*[16] *= Gross PPE − Accumulated Depreciation.* This represents physical capital in the models.
8. Net Patent and Copyright Expenses: the net book value of intangible assets like patents, copyrights, and trademarks after accounting for amortization and impairments.
9. Total Liabilities: all financial obligations excluding shareholders' equity. It is calculated as: *Total Liabilities = Equity and Liabilities − Shareholders' Equity*

To assess market concentration, we construct the Herfindahl–Hirschman Index (HHI) and the Concentration Ratio of the top eight firms (CR8) based on total sales values. For the HHI, we first calculated each firm's market share within a two-digit industry in a given year, defined as:

$$share_{it} = \frac{Sales_{it}}{Total\ industry\ Sales_t} \qquad [12]$$

Here, $share_{it}$ denotes the share of the sales of firm i at time t; $Sales_{it}$ is the sales of firm i in time period t; and $Total\ industry\ Sales_t$ is the total sales of all firms of the respective industry at time t. The HHI for each industry-year combination was then obtained by summing the squared sales shares of all firms.

[15] Change in stocks = closing stock – opening stock, i.e., differences in terms of inventories such as raw materials, stores and spares, etc.
[16] PPE is property, plant and equipment.

For intellectual property rights (IPR) enforcement, we employed our de facto IPR index. The dataset is an unbalanced panel across 27 industries over the period 1970–2020, with observations recorded at five-year intervals. After excluding missing data[17], the panel consists of 133 industry-year observations.

All monetary variables, including Total Sales, R&D Expenditure, Staff Welfare and Training Expenses, Selling and Distribution Expenses, and Profit After Tax (PAT), were deflated using the Wholesale Price Index (WPI) released by the Department for Promotion of Industry and Internal Trade (DPIIT, 2025) with base[18] (2011-12) = 100.

We have further taken the log of all the variables. However, to handle variables with negative or zero values, especially in profitability or asset-related metrics, we applied the Inverse Hyperbolic Sine (IHS) transformation[19] instead of the natural logarithm. This method preserves negative values and avoids data loss due to log transformation limitations, while maintaining interpretability similar to that of a logarithmic scale.

7. Estimation Strategy

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[17] We have treated the missing observation and discussed the details in the next section.

[18] Given the existence of WPI data in multiple base years (1981–82, 1993–94, 2004–05, and 2011–12), we have to rebase the index to a common reference year of 2011–12. For this, a chained linking method was employed using overlapping year values to compute linking factors between consecutive base year revisions. The procedure involved identifying transitions between base years and calculating linking factors as the ratio of index values from the same overlapping year across the old and new base series. Where multiple overlapping years were available, average ratios were used to smooth year-specific fluctuations. These factors were then applied sequentially to convert earlier series to the 2011–12 base. Specifically, the 1981–82 series was adjusted using three factors ($LF_1 \times LF_2 \times LF_3$), the 1993–94 series using two ($LF_2 \times LF_3$), and the 2004–05 series using one (LF_3), while the 2011–12 series required no adjustment. The harmonized WPI series was then integrated into a continuous time series expressed uniformly in 2011–12 prices, enabling consistent deflation of nominal variables for subsequent regression analyses. To align the rebased WPI series with the Prowess industry classification, we concorded WPI industry categories to the NIC (2008) two-digit codes. This methodological approach ensures internal price-base consistency, preserves real growth and inflation dynamics, and aligns with standard practices recommended by the Reserve Bank of India (RBI), the Ministry of Statistics and Programme Implementation (MOSPI), and contemporary macroeconomic panel research. Preference was given to newer base year values, particularly the 2011-12 base, due to their incorporation of updated commodity weights, improved market representativeness, and reduced chaining errors. Fewer linking steps inherently minimize error propagation in the deflation process. This mirrors the approach adopted by Indian statistical agencies, where older base series are truncated after the final overlapping year, and newer base series are used onward. For sectors lacking disaggregated WPI data, the 'All Commodities' WPI index served as a general deflator to maintain cross-sectoral consistency. For the 2011–12 base year, disaggregated product-level indices were utilized where available, while earlier series relied on aggregated product categories due to data constraints. In some instances, WPI aggregate such as the combined "Food and Beverages" category was used to deflate the respective individual industries in Prowess.

[19] $\text{asinh}(x) = \ln(x + \sqrt{x^2 + 1})$

This study employs a fixed effects panel regression model[20] to account for both industry-specific and temporal unobserved heterogeneity in the dataset. The fixed effects approach is particularly well-suited for panel data, as it controls for time-invariant unobservable characteristics across entities (in this case, industries) that could otherwise bias the estimation results. By de-meaning or differencing the data, the model focuses on within-industry variations over time, thus isolating the impact of the independent variables on the dependent variables while holding constant any unobserved heterogeneity. Additionally, incorporating year fixed effects allows us to account for macroeconomic shocks or policy changes common to all industries in a given year (Wooldridge, 2010; Greene, 2012). In the context of our study, the fixed effects model is essential to accurately estimate the causal relationship between changes in intellectual property rights (IPR) regimes and various industry-level outcomes such as sales, R&D spending, and profitability while controlling for unobserved industry characteristics that do not change over time.

To mitigate the loss of observations and improve balance, we interpolated the IPR index for missing years within the 1990–2020 period using five-year intervals consistent with the structure of the Prowess data. After these adjustments, the resulting panel consists of 27 two-digit industries observed over seven time periods (1990–2020, at five-year intervals), totalling 185 industry-year observations. To further preserve degrees of freedom in estimation, we grouped the 27 industries into six broader industry categories (as shown in Table 2), coded as dummy variables in the fixed effects specification. These groups are:

1. <u>Primary</u> – including agriculture and allied sectors
2. <u>Light Manufacturing</u> – including food, beverages, tobacco, textiles, apparel, leather, wood, rubber, paper, and similar low-capital-intensive sectors
3. <u>Heavy Manufacturing</u> – encompassing chemicals, petroleum, machinery, electrical equipment, fabricated metals, motor vehicles, and other capital-intensive sectors
4. <u>Computer and IT Services</u> – including software publishing, IT consulting, broadcasting, and related services
5. <u>Other Services</u> – covering accommodation, real estate, and creative industries
6. <u>Health and Pharma</u> – capturing pharmaceutical and life sciences industries

For robustness, we repeated all regressions using the standard two-digit industry and year fixed effects specification, with standard errors clustered at the two-digit industry level.

[20] We ran Hausman specification test to ensure that the fixed effects model should be preferred over random effects model. Test's chi square value is 41.316 with p value equals to 0.00 indicating to reject the null hypothesis stating random effects model is better.

The results were qualitatively consistent with our grouped-industry approach, indicating that the grouping strategy does not distort the inference.

A key focus of the analysis is to explore whether the impact of IPR strengthening differs across industries with varying levels of R&D intensity. Industries with higher R&D intensity may exhibit stronger responses, either positively or negatively to changes in the IPR regime. To capture this heterogeneity, we created a binary indicator for R&D intensity. First, we computed R&D intensity as the ratio of R&D expenditure to total sales for each industry-year:

$$R\&D\ intensity_{it} = \frac{R\&D\ expenditure_{it}}{Sales_{it}} \qquad [13]$$

We then defined a high R&D dummy that takes the value 1 if an industry's R&D intensity in a given year is greater than or equal to the median R&D intensity across all industries for that year, and is 0 otherwise. This variable varies across both industries and time and is used to interact with the IPR variable in the regression model. The interaction term allows us to test for differential treatment effects across industries with varying innovation intensity. In addition to this binary classification, we also examine the effects of IPR policy across industries dominated by specific intellectual property instruments, namely patents, copyrights, and trademarks. We categorize industries into these three groups as shown in Table 3, based on which form of IP is most prevalent in their innovation output.

Accordingly, three dummy variables are constructed: one each for patent-intensive, copyright-intensive, and trademark-intensive industries, with values of 1 assigned based on the dominant IP form, and 0 otherwise.

Further, to assess heterogeneity across broader industrial structures, we estimated separate regressions for each of the six industry groups defined earlier. In each regression, we interacted the IPR variable with the respective industry group dummy to examine whether stronger IPR protection has heterogeneous effects on sales, R&D, and profitability across different sectors. This approach recognizes that the benefits (or costs) of IPR reform may not be uniform and could be shaped by sector-specific characteristics such as capital intensity, innovation patterns, and exposure to global competition.

With the model and data preparation in place, we now turn to the descriptive statistics and summary results, which provide a foundation for interpreting the regression outcomes in the next section.

8. Descriptive Results

Table 4 presents the descriptive statistics for all variables utilized in the study across various analytical segments. A comparison of industry-level averages reveals that industries classified as high R&D intensive exhibit nearly double the average real sales relative to those categorized as low R&D intensive. The de facto IPR index is also, on average, 0.14 points higher in high R&D industries, indicating that intellectual property rights are enforced more stringently in sectors with elevated R&D activity. Furthermore, profit after tax (PAT) is, on average, approximately 6 percentage points higher in high R&D industries compared to their low R&D counterparts. Similarly, the return on assets (ROA) is observed to be approximately three times greater in high R&D intensive sectors, suggesting enhanced profitability and asset efficiency in industries with a strong emphasis on innovation.

Table 5 offers a comparative view of summary statistics across patent, copyright, and trademark-intensive industries. The data reveal that average real sales are highest in patent-intensive industries, exceeding those of both copyright- and trademark-intensive sectors. In terms of intellectual property enforcement, the de facto IPR index records its highest values in patent-intensive industries, followed sequentially by copyright and then trademark-intensive sectors, suggesting a gradient in IPR stringency. R&D expenditure also peaks in patent-intensive industries, aligning with expectations given their innovation-driven nature. Notably, average profit after tax in patent-intensive sectors is approximately 19 times greater than in copyright-intensive industries and 10 times greater than in trademark-intensive industries.

These patterns collectively suggest that industries with higher R&D expenditure and a dominant reliance on patent protection experience significantly greater returns in both sales and profitability. This evidence further implies that the impact of IPR strengthening is likely heterogeneous, potentially varying not only between high and low R&D intensity industries but also across different IP instrument intensities.

Finally, Table 6 summarizes the key variables across broader industry classifications, offering insights into sector-level patterns. The data indicate that average real sales are highest in the heavy manufacturing and pharmaceutical sectors. The pharmaceutical industry, in particular, reports the highest average R&D intensity at 0.027, surpassing all other industry groups. In terms of profitability, both pharmaceutical and heavy manufacturing industries show the highest average PAT among the broad sectors. However, when examining the implementation of IPR of the primary sector, which includes agriculture we got that it records the lowest average index value at 0.353, reflecting a comparatively lower demand for IP protection in such resource-based industries. By contrast, the IPR implementation index for other industry groups ranges from 0.4 to 0.6, reflecting moderate to strong enforcement levels consistent with their innovation needs and IP reliance.

Figure 2 shows a closer examination of the average trends across industries reveals important sectoral heterogeneity in intellectual property rights (IPR) enforcement, sales performance, R&D intensity, and profitability. These visual insights not only provide an empirical foundation for our analysis but also reinforce the conceptual argument that the effects of IPR protection are shaped by underlying industry characteristics. As illustrated in Panels (a) and (b) of Figure 2, the average de facto IPR implementation varies substantially across both two-digit industries and broader industry groups. Among the two-digit sectors (as shown in Panel (a)), petroleum products, pharmaceuticals, and fabricated metals exhibit the highest levels of IPR enforcement, with index values approaching or exceeding 0.7 to 0.8. In contrast, industries such as crop and animal production, textiles, and food processing report relatively lower average IPR values, ranging between 0.2 to 0.4, suggesting weaker enforcement or lower relevance of formal IP mechanisms in these sectors.

When aggregated into broader categories Panel (b) of Figure 2, the primary sector (comprising mainly agriculture-related industries) stands out with the lowest average IPR enforcement level (≈0.35), reflecting its relatively limited dependence on formal intellectual property mechanisms, likely due to lower innovation intensity and weaker institutional integration (Lall, 2003). Conversely, light manufacturing, heavy manufacturing, and pharmaceutical and health-related sectors report consistently higher IPR enforcement, with mean values ranging from 0.45 to 0.6, indicating stronger reliance on IP protection regimes in innovation- and capital-intensive industries. These patterns confirm the findings in institutional literature that emphasize the uneven reach and implementation of IPRs across different sectors (Park & Lippoldt, 2008; Qian, 2007).

Panel (c) and (d) of Figure 2 show average log real sales over time across industries. At the two-digit level (in Panel c), pharmaceuticals, petroleum products, and motor vehicles emerge as top performers in terms of average industry sales (log values around 14 to 15), indicating high output and market scale. On the other hand, industries like textiles, tobacco products, leather, and creative arts report substantially lower average sales, reflecting either comparable smaller market sizes, low scalability, or fragmented market structures. When examined at the aggregate industry-group level illustrated in Panel (d), the heavy manufacturing and health and pharma categories exhibit the highest average log real sales, followed by IT services and light manufacturing. In contrast, the primary sector continues to show relatively low average sales levels. This reaffirms the idea that IP-intensive and innovation-driven sectors tend to be market-dominant, both in terms of output volume and firm-level revenues (Schmoch et al., 2003).

Panel (a) and (b) of Figure 3 shows the mean R&D intensity, measured as the ratio of R&D expenditure to total sales. A striking concentration of R&D activity is evident in pharmaceuticals, which stand out distinctly with an average R&D intensity exceeding 0.03, significantly higher than all other two-digit industries. Other sectors with relatively elevated R&D intensity include medical instruments, machinery and equipment, and IT-related services, albeit at a much lower scale. At the broader industry-group level as shown in Panel (b), the Health & Pharma sector shows the highest R&D intensity by a wide margin (≈0.027), followed by heavy manufacturing and IT services, each reporting modest levels of innovation investment. In contrast, primary, light manufacturing, and other services sectors show very limited R&D spending. This strongly aligns with literature that documents sector-specific disparities in innovation investment and reliance on formal intellectual property regimes (Mansfield, 1994; Cohen et al., 2000).

Panel (c) and (d) of Figure 3 highlights the distribution of average profit after tax (PAT) across industries. The pharmaceuticals and petroleum products sectors again dominate, with substantially higher mean PAT values, in some cases exceeding 1,000,000 INR in real terms. Industries such as tobacco, motor vehicles, and electrical machinery also perform strongly. In contrast, sectors such as tanning and dressing of leather, textiles, and broadcasting show much lower or even negative average PAT, indicating either structural inefficiencies or market competition effects. Aggregated by industry group as given in Panel (d), Health & Pharma once again leads with the highest average profitability, followed by heavy manufacturing and IT services. The primary and light manufacturing sectors display relatively weak profitability figures. The data indicate that industries characterized by high R&D intensity and stronger IPR enforcement are also those with higher average profitability, suggesting a positive link between innovation, institutional quality, and financial performance (Hall et al., 2007).

Taken together, these findings reveal a clear pattern: industries that are innovation-intensive and reliant on formal IPR mechanisms notably, pharmaceuticals, chemical manufacturing, and advanced machinery consistently outperform others in terms of R&D investment, sales volume, and profitability. These industries also enjoy stronger de facto IPR enforcement, supporting the hypothesis that IPRs matter more where innovation is central to business strategy. Conversely, sectors with low R&D intensity and weaker institutional environments, such as agriculture, textiles, and traditional services report lower sales, weaker profitability, and less IPR engagement. These patterns set the stage for investigating the causal and heterogeneous effects of IPR strengthening across different industrial contexts in next sections.

9. Estimation results:

9.1 Fixed effects model using Broad Industry Groups

Table 7 shows the results for the fixed effects model using dummies for the broader industry groups[21] as entity fixed effects[22]. The results in this table are based on the clustered robust standard errors. Panel (1) of Table 7 shows the baseline results of the sales model; we show positive but insignificant effect of IPR strengthening on the industry sales. The insignificant aggregate results may indicate that there could be a role of potential heterogeneity. To deal with this, we have introduced an interaction term of IPR and high R&D dummy[23].

Panel (2) of Table 7 shows the negative and highly significant coefficient on the interaction term ($IPR_{it-1} X\ HRD_{it}$= –0.523, p < 0.01) which reveals a moderating effect: the impact of IPR on sales diminishes as a firm's R&D intensity increases. This suggests that while firms with lower R&D intensity benefit more from stronger IPR environment, the marginal gains from IPR protection are reduced for firms that are already heavily engaged in R&D. The negative and significant interaction term may also reflect a strategic shift in firm behavior rather than a decline in performance. In environment with stronger IPR protection, R&D-intensive firms may leverage their enhanced exclusivity to engage in monopoly pricing, reduce output, or delay commercialization which are all rational strategies under IP-backed market power (Gilbert and Shapiro, 1990). These firms may not need to expand sales volumes if stronger IPR regime enables them to extract greater rents per unit sold. This outcome aligns with theoretical models of strategic innovation, where firms trade off quantity for long-run market positioning and intellectual property accumulation (Gallini, 2002). Thus, the observed decline in sales under stronger IPR for high-R&D firms should not be interpreted as inefficiency, but as a reflection of their ability to exploit institutional advantages in innovation-driven markets.

This helps explain the observed negative interaction between IPR and high R&D intensity: stronger IPR may enable firms to shift away from volume-based strategies toward higher-margin, IP-secured market positions (Boldrin & Levine, 2013).

[21] We have further done the robustness check using the general fixed effects with all the 27 two-digit industry dummies with year fixed effects.
[22] With additional year dummies to control for common time shocks.
[23] As discussed above, high R&D dummy takes value 1 if an industry's R&D intensity in a given year is greater than or equal to the median R&D intensity across all industries for that year, and is 0 otherwise.

Other variables such as lagged R&D expenditure shows a positive and significant impact on industry total sales, meaning last year's expenditure on research and development significantly increase the real sales of this year. This is because R&D typically requires time to yeild commercial benefits, as knowledge generates through R&D is first transformed into new products, processes, or improvements that later enters the market. Moreover, prior R&D spending enhances the firm's knowledge stock and absorptive capacity, which strengthens competitiveness and translates into revenue growth in subsequent years (Griliches, 1998; Hall and Mairesse, 1995).

We have found that on an average, a 1% increase in total liability increases the total sales by around 0.73% in the baseline model (Column 1) and by 0.72% in the interaction model (Column 2). Both the results are significant at 1% level. These positive and significant coefficients suggest that improvement in sales is highly influenced by greater access to financial resources. Access to financial resources allow firms to channel investment into operations and growth initiatives, which in turn supports higher sales (Modigliani et. al., 1958).

Moreover, selling and distribution expenses, such as on marketing, advertisement and distribution activities, stimulate real sales, such that a 1% increase in this expenditure improves sales by around 0.33% in the baseline model (Column 1) and by around 0.32% in the interaction model (Column 2). These coefficients are also significant at 1% level.

Columns (3) and (4) in Table 7 examine the influence of intellectual property rights (IPR) on firms' R&D investment[24]. In Column (3), the baseline model shows a positive but statistically insignificant effect of IPR alone. One possible reason for this unexpected insignificance is that IPR at an aggregate level, may not adequately reflect sector-specific R&D expenditure[25]. For instance, stronger IPR protection may disproportionately benefit large pharmaceutical firms, which rely heavily on patent-based appropriability, but provide little incentive for other sector firms such as agriculture, construction, etc., in the same dataset. This aggregation effect can dilute the overall significance of IPR. Furthermore, the result points toward underlying heterogeneity across industries: sectors that are already innovation-intensive (with high baseline R&D) may respond to stronger IPR by further increasing research

[24] In panel fixed effects with broader industry fixed effects, we have not taken $lnR\&D_{t-1}$ as an explanatory variable in column (3) and (4). It is because including lagged R&D is soaking up the significance of other significant variables such as net patent and copyright expense while the significance level of the interaction term ($IPR_{it-1} X\ HRD_{it}$) remained intact with or without lagged R&D term being included (showing our result is robust in both conditions). However, lagged R&D is taken in Table 8 because no such problem is detected there.

[25] We have analyzed the sector-specific results in the later sub-sections.

spending, while low-R&D industries may show little or no response. Such asymmetry explains why IPR's direct effect may not emerge as significant when estimated at a broad level.

Column (4) introduces an interaction term between IPR and R&D intensity ($IPR_{it-1} X\ HRD_{it}$), and reveals a more nuanced relationship: the interaction term is strongly positive and significant (3.656, $p < 0.01$), with a positive and statistically significant net effect ($\beta_1 + \beta_2$). This implies that the positive impact of IPR on R&D spendings is disproportionately stronger for firms that already engage heavily in R&D. Stronger IPR provides monopoly rents, higher appropriability, and stronger incentives to them. These findings are theoretically consistent with Cohen and Levinthal (1990), which posits that firms with greater internal knowledge stocks are better equipped to recognize, assimilate, and exploit external protections such as patent laws. On including the interaction term, the aggregate effect of IPR becomes negative and significant at 10% level. This actually shows the effect of IPR strengthening in case of low-R&D intensive industries. Stronger IPR reduces R&D incentives in low-R&D industries because they often depend on external knowledge, reverse engineering, or tech transfer and stricter protection cuts off these channels. Additionally, lagged sales and the stock of patents are also positively associated with R&D spending, highlighting the importance of firm scale and innovation assets in driving R&D behavior.

Columns (5) and (6) of Table 7 focus on the relationship between IPR protection and firm profitability, measured using average return on assets (ROA). In the baseline specification (Column 5), $lnIPR_{it-1}$ has a positive and significant effect (0.391, $p < 0.05$), suggesting that overall industries with stronger IPR regimes enjoy higher profitability. This effect diminishes and becomes statistically insignificant (0.0765) when the interaction term is added in Column (6). However, the interaction term $IPR_{it-1} X\ HRD_{it}$ remains positive and significant (1.079, $p < 0.05$), with a positive and statistically significant net effect ($\beta_1 + \beta_2$) indicating that firms with higher R&D intensity experience greater profitability gains from stronger IPR protections. These results are consistent with theories in strategic management and innovation economics, which argue that effective appropriation mechanisms, like patent enforcement enables innovative firms to capture the rents from their technological advantages (Teece, 1986; Levin et al., 1987).

Moreover, the positive and significant coefficients on past sales (0.604) and R&D (0.278) further reinforce the notion that innovation and market strength are important drivers of profitability. Conversely, a strong negative effect of market concentration (HHI) on ROA suggests that firms in more competitive industries tend to perform better, likely due to efficiency pressures which relates with the Schumpeterian ideology. Meanwhile, the number of firms in the industry has a consistently negative and significant effect on ROA, possibly indicating that increased competition lowers margins[26]. Together, the results are consistent with the "inverted-U" view that both excessive concentration and excessive competition can reduce performance (Aghion et. al., 2005; Aghion & Griffith, 2008). Interestingly, the net patent and copyright book value have a positive and significant relationship with both R&D (0.230, $p < 0.01$) and ROA (0.173, $p < 0.01$) in Columns (4) and (6), which reinforces the value of patenting as both a signal of innovation and a source of competitive advantage (Hall & Ziedonis, 2001).

Overall, the interaction results across Columns (4) and (6) emphasize a nuanced story: IPR protection on its own has limited effect, but becomes a powerful driver of both R&D and profitability when pairs with high industry's internal innovation capacity. For both R&D investment and profitability, the positive interaction indicates that firms with higher R&D intensity derive greater benefits from stronger IPR regimes. This underscores the importance of firm-level absorptive capacity in leveraging institutional frameworks for competitive advantage (Cohen & Levinthal, 1990). On the other hand, in the case of sales (Column 2), stronger IPR appears to benefit firms with lower R&D intensity more, suggesting that such firms may rely on external protection mechanisms to commercialize or appropriate innovations. This may also reflect the strategic output reduction by high R&D firms to gain from monopoly power. This implies that IPR not only safeguards return on innovation but also reinforces the strategic value of internal R&D, enhancing both innovation input and financial performance.

To ensure robustness, we employ cluster-robust standard errors at the two-digit industry level as shown in Table 8, which provide more conservative but reliable inference, accounting for within-industry correlation over time. Table 8 indicates similar results as we got in Table 7. The interaction term of IPR and R&D has a negative and significant impact on sales, positive and significant impact on R&D. We got an insignificant impact on profitability; however, the sign of the coefficient is positive reflecting the similar tendencies of the variable. All the other control variables are almost having similar signs and significance establishing the robustness.

[26] For more clarity, HHI and the number of firms capture different aspects of competition. High concentration (high HHI) may lower profitability due to inefficiency or weak innovation pressures, while too many firms erode margins through rivalry.

9.2 Exploring Heterogeneities across Patent, Copyright and Trademark industries

We have tried to explore the results across different heterogeneities in case of patent, copyright and trademark intensive industries. Table 9 provides insight into how the effect of IPR strengthening on R&D investment varies across industries with different forms of intellectual property dependence; namely patent, copyright, and trademark intensities. Table 9 shows the R&D model showing the differential effects of patent, copyright and trademark intensive industries using the broad industry groups as fixed effects with year dummies. The interaction term $IPR_{t-1}\ X\ Patent$ reveal a differentiated pattern in patent-intensive industries, the positive and significant interaction between IPR and patent reliance suggests that stronger IPR regimes stimulate R&D investment, supporting theories that emphasize the role of enforceable patents in protecting returns from technological innovation (Teece, 1986; Levin et al., 1987). In contrast, the interaction effects in copyright and trademark intensive sectors are negative and statistically significant, implying that stronger IPR regimes may deter R&D investment in these industries. This counterintuitive result aligns with literature suggesting that overly rigid enforcement, especially in cultural and branding sectors, may inhibit creative freedom, increase transaction costs, or disincentivize cumulative innovation (Boldrin & Levine, 2008).

Regarding the aggregate IPR variable ($lnIPR_{t-1}$), its positive and significant coefficients in copyright and trademark intensive sectors suggest that IPR environments broadly encourage R&D across these sectors, but only up to a point beyond which stronger protections might impose constraints. Across all models, the stock of net patents ($NetPatcop_t$) emerges as a consistently positive and significant predictor of R&D, reinforcing the role of patent portfolios as both innovation inputs and signals of absorptive capacity (Cohen & Levinthal, 1990). Additionally, past sales are positively associated with R&D in patent and trademark-intensive industries, suggesting that firm scale and market performance underpin innovation investment. Collectively, the findings highlight that the design and scope of IPR policy must be sensitive to industry-specific innovation dynamics, as a uniform strengthening of rights may yield uneven effects across different creative and technological domains.

Table 10 investigates how the effect of IPR protection on firm profitability is conditioned by the type of intellectual property predominance across industries. The results show that the interaction between IPR strength and industry-specific IP intensity is positive and significant in patent and copyright intensive sectors, indicating that stronger IPR environments enhance profitability when aligned with the core assets of technological or creative industries. These findings support the view that formal protections are crucial for capturing returns on innovation and creative content (Teece, 1986; Levin et al., 1987). In contrast, the interaction effect is negative and significant in trademark-intensive industries, suggesting that overly strict IPR enforcement may constrain profitability in brand-driven sectors, potentially due to increased legal costs or reduced flexibility in market signaling. Trademarks are often easier to imitate and markets like apparel, shoes, bags, etc., are locally dominated by imitation of big brands. That's why, when IPR strengthens, trademark dominated industries may face a downward leap in the profitability. The aggregate IPR variable, meanwhile, is either negative or insignificant across the models, implying that broad IPR protection alone does not guarantee improved performance it is the strategic alignment with industry-specific intangible assets that determines its effectiveness. Other notable results include the positive effects of lagged R&D and sales on profitability, and the consistently negative role of tangible assets and industry competition, further underscoring the growing importance of intangible and innovation-driven value creation. We have also done the results for the sales model, but we did not find any significant differential effect for the same.

9.3 Different Heterogeneities across Broad Industry Sectors

Table 11 shows the sales regressions interacted with broad industry groups. Results show that IPR regimes have heterogeneous effects across sectors, depending on the nature of value creation. The aggregate effect of IPR is generally positive across all industries, albeit mostly insignificant. However, the interaction effects tell a more nuanced story.

IPR protection has a negative and significant effect in the computer & IT sector, indicating that overly stringent IPR may hinder sales performance in industries dependent on cumulative innovation or rapid product cycles. Conversely, in other services such as creative arts, the interaction effect is strongly positive, suggesting that stronger IPR enhances market performance where service offerings are more vulnerable to imitation[27]. Sales performance is consistently and positively driven by R&D, skilled labor ($ln\ Stftrainwelf_t$), and marketing and distribution ($ln\ SDexp_t$), underlining the importance of innovation capabilities and global exposure in sustaining revenues. These patterns reinforce that IPR alone does not guarantee higher sales, its effectiveness is shaped by the sector's innovation structure and commercial strategy.

Table 12 shows the R&D regressions across different sector heterogeneities. Results demonstrate that the incentive effect of IPR on innovation investment is highly industry-

[27] In creative arts, innovator tends to restrict the sales in case of weak protection as creative designs and literary work is very vulnerable to imitation.

specific. While the aggregate impact of IPR on R&D is insignificant across most sectors, the interaction effects reveal critical distinctions. In Heavy Manufacturing and Health & Pharma, the interaction of IPR with sector identity is significantly positive, suggesting that firms in these industries respond to stronger IPR regimes with increased innovation investment. This is theoretically consistent with the idea that firms in science-based or technologically intensive sectors depend heavily on formal protection to secure returns on R&D (Teece, 1986; Cohen & Levinthal, 1990). In contrast, the Primary sector exhibits a significant and negative interaction, implying that stricter IPR regimes may suppress innovation in resource-based industries, possibly due to higher entry barriers or limited appropriability. Across all sectors, net patent stock remains a robust predictor of R&D activity, highlighting the role of prior innovation as both input and signal.

Table 13 depicts the profitability regressions across sectoral heterogeneities. Results further clarify how the alignment between IPR regimes and industry type conditions firm performance. While the direct effect of IPR is largely insignificant, the interaction terms point to differentiated outcomes. In Light Manufacturing and Health & Pharma, IPR interaction terms are significantly positive, indicating that stronger protection regimes translate into higher profitability where brand value or proprietary knowledge plays a central role. Conversely, the Primary sector experiences a sharp negative interaction, suggesting that stringent IPR may depress profits, likely due to increased compliance burdens or reduced competition.

Control variables such as sales and net patent stock are consistently positive across industries, reaffirming the importance of scale and innovation in driving profitability, while sectoral competition (number of firms) and expenditure on tangible assets negatively influence returns.

Overall, across the three models, a consistent pattern emerges: IPR effectiveness is highly context-dependent, shaped by the innovation profile, appropriability conditions, and strategic structure of each industry. Stronger IPR regimes boost R&D and profitability in innovation-intensive sectors like pharmaceuticals and advanced manufacturing but may constrain performance in primary and IT-based sectors where openness and incremental innovation are more critical. IPR is most effective not as a universal tool but as a complementary institution, yielding optimal outcomes when aligned with sector-specific dynamics and internal firm capabilities.

10. Conclusion

This paper has explored how intellectual property rights, though governed by a common legal framework, are implemented unevenly across industries in practice. While prior studies have largely relied on national-level legal indices to assess IPR strength, they often overlook how laws are enforced on the ground and how such enforcement varies by sector. Recognizing this gap, the paper introduced a novel, industry-wise de facto IPR implementation index for India, offering a more grounded and dynamic view of IPR enforcement from 1970 to 2020. The analysis reveals clear variation in implementation patterns across industries, shaped by differences in legal engagement, technological intensity, and the evolving nature of each sector. These findings underscore the importance of moving beyond a one-size-fits-all approach to studying IPRs, and instead accounting for the lived realities of enforcement within industries.

We found that overall, that IPR strengthening based on de facto index leads to a positive and significant effect on all three industry specific outcomes i.e., sales, innovation and profitability when we introduce the interaction effects of IPR strengthening with high R&D dummy. However, the interaction term itself shows the heterogeneous effects of IPR strengthening on sales, R&D and profits in case of industries indulging in high R&D. one percentage point increase in the last year's IPR strengthening cause around 52% decrease in this year's sales for those industries which are involved in high R&D intensity as compared to low R&D intensities, on an average. This might mean less marginal increase or strategic output decline to gain monopoly power. In other cases of R&D and profitability, the interaction term is positive and significant, reflecting that a further strengthening of IPR stimulate further innovation and promotes profits for those industries which involve in high R&D as compared to those with low R&D intensity. This reflects that for high R&D intensive industries, stricter IPR leads to more innovation and profits but may not stimulate sales which means that profits are generating from scares supply and more prices due to increased monopoly power. Other robustness estimations also support these results.

Allowing for further disaggregated heterogeneities, we get differentiated impacts based on different types of industries. Overall, industries such as pharmaceuticals gain through strict IPR implementations in terms of profitability and innovation while, industries such as agriculture lose through strict IPR implementation. In terms of sales, other services like creative arts gains through strict IPR strengthening. Similarly, patent intensive industries gain in terms of innovation and profits through strict IPR implementation while trademark intensive industries lose.

Overall, these findings highlight the need for a more nuanced and sector-specific understanding of IPR policy impacts. While stronger enforcement can drive innovation and profitability in certain sectors, it may simultaneously constrain output or access in others. This nuanced view is critical for designing balanced IPR policies that support innovation while minimizing adverse effects across different segments of the economy.

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Table 1
Frequency Distribution of Patents, Copyrights and Trademarks Infringement Cases by Industry

Industry	**Patents**		**Copyrights**		**Trademarks**	
	Freq.	**(%)**	**Freq.**	**(%)**	**Freq.**	**(%)**
Air and spacecraft and related machinery	1	1.96				
Basic chemicals, fertilizer and nitrogen compounds	8	15.69			5	1.88
Basic iron and steel					1	0.38
Basic precious and other non-ferrous metals					1	0.38
Beverages					14	5.26
Computer programming, consultancy and related acti.					8	3.01
Construction of buildings					2	0.75
Consumer electronics	1	1.96			17	6.39
Creative, arts and entertainment activities			48	49.5	6	2.26
Dairy products					1	0.38
Data processing, hosting and related activities; web portals			1	1.03		
Domestic appliances	1	1.96			3	1.13
Electric motors, generators, transformers and electricity	4	7.84			2	0.75
Electric power generation, transmission and distribution	1	1.96				
Electronic components					1	0.38
Food products	1	1.96				
Footwear					3	1.13
Games and toys	2	3.92				
General-purpose machinery	1	1.96			10	3.76
Growing of non-perennial crops	2	3.92			3	1.13
Jewellery, bijouterie and related articles					1	0.38
Management consultancy activities					1	0.38
Measuring, testing, navigating and control equipment;					2	0.75
Medical and dental instruments and supplies					1	0.38
Motion picture, video and television programme active.			1	1.03		
Motor vehicles	2	3.92			10	3.76
Other chemical products					23	8.65
Other electrical equipment	1	1.96				
Other fabricated metal products; metalworking service					3	1.13
Other food products					25	9.39
Other manufacturing					4	1.5
Other personal service activities					1	0.38
Other social work activities without accommodation					2	0.75
Other textiles					1	0.38
Pharmaceuticals, medicinal chemical and botanical	17	33.33			38	14.29
Plastics products	1	1.96				
Printing and service activities related to printing			2	2.06	4	1.5
Products of wood, cork, straw and plaiting materials					7	2.63
Publishing of books, periodicals and other publishing activities			18	18.6	8	3
Real estate activities with own or leased property					11	4.14
Refined petroleum products	1	1.96			9	3.38
Rubber products					2	0.75
Short term accommodation activities					4	1.5
Software publishing			11	11.3		
Specialized design activities			1	1.03		
Special-purpose machinery	2	3.92			3	1.13
Spinning, weaving and finishing of textiles					1	0.38
Structural metal products, tanks, reservoirs and steam					1	0.38
Tanning and dressing of leather; manufacture of luggage, bags	1	1.96			2	0.75
Telecommunication	4	7.84				
Television programming and broadcasting activities			15	15.5	2	0.75
Tobacco products					3	1.13
Transport equipment					1	0.38
Travel agency and tour operator activities					1	0.38
Vegetable and animal oils and fats					2	0.75
Wearing apparel, except fur apparel					16	6.02
Total	51	100	97	100	266	100

Table 2
Classification of Two-digit industries into Six Broad Categories

Primary	Light Mfg.	Heavy Mfg.	Computer and IT Services	Other Services	Health and Pharma
Crop and animal production (01)	Manufacture of food products (10)	Manufacture of coke and refined petroleum products (capital-intensive, less IP-intensive) (19)	Computer programming, consultancy and related activities (62)	Accommodation (55)	Manufacture of pharmaceuticals (21)
	Manufacture of beverages (11)	Manufacture of basic metals (some patent use, less IP-focused) (24)	Publishing activities (58)	Real estate activities (68)	
	Manufacture of tobacco products (12)	Manufacture of fabricated metal products (depends on product specifics) (25)	Broadcasting and programming activities (60)	Creative, arts and entertainment activities (90)	
	Manufacture of textiles (13)	Manufacture of computer, electronic and optical products (26)	Telecommunications (61)		
	Manufacture of wearing apparel (14)	Manufacture of electrical equipment (27)			
	Manufacture of leather and related products (15)	Manufacture of machinery and equipment (28)			
	Manufacture of wood and products of wood (16)	Manufacture of motor vehicles, trailers and semi-trailers (29)			
	Manufacture of rubber and plastics products (22)	Manufacture of chemicals and chemical products (20)			
	Printing and reproduction of recorded media (18)	Other manufacturing (32)			

Note: Two-digit NIC codes in the brackets

Table 3 **Differentiating among two-digit industries based on Patent, Copyright, and Trademark intensive industries**			
Patent-Intensive Industry	**Copyright-Intensive Industry**	**Trademark-Intensive Industry**	**Neutral-Industry**
Manufacture of chemicals and chemical products (20)	Printing and reproduction of recorded media (18)	Manufacture of food products (10)	Crop and animal production (some trademark use, low IP intensity) (01)
Manufacture of pharmaceuticals (21)	Publishing activities (58)	Manufacture of beverages (11)	Manufacture of coke and refined petroleum products (capital-intensive, less IP-intensive) (19)
Manufacture of computer, electronic and optical products (26)	Broadcasting and programming activities (60)	Manufacture of tobacco products (12)	Manufacture of basic metals (some patent use, less IP-focused) (24)
Manufacture of electrical equipment (27)	Creative, arts and entertainment activities (90)	Manufacture of textiles (13)	Manufacture of fabricated metal products (depends on product specifics) (25)
Manufacture of machinery and equipment (28)		Manufacture of wearing apparel (14)	
Manufacture of motor vehicles, trailers and semi-trailers (29)		Manufacture of leather and related products (15)	
Computer programming, consultancy and related activities (62)		Manufacture of wood and products of wood (16)	
		Manufacture of rubber and plastics products (22)	
		Other manufacturing (32)	
		Accommodation (55)	
		Telecommunications (61)	
		Real estate activities (68)	
Source: European Patent Office[28].			

[28] https://www.eusemiconductors.eu/sites/default/files/uploads/201309_EPO-OHIM_IPIntensiveIndustries.pdf#page=90.14

Table 4
Summary Statistics

Variable	Overall		High R&D Intensity		Low R&D Intensity	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Real Sales	1349018.3	2638805.5	1813557.4	3027188	858671.4	2060059.8
Industry IPR index	.542	.264	.62	.251	.459	.254
Net tangible assets	458294.41	1042756.4	602160.2	1252432.7	306436.07	738825.05
Staff welfare and training expense	4724.232	9425.994	7574.219	12195.063	1715.912	2965.185
R&D expenditure	4248.455	13860.192	8003.467	18603.071	284.831	840.58
Total liabilities	1561402	3152003	2107495.2	3647011.4	984970.31	2416149.4
Net patents and copyright	830.316	3550.694	1409.103	4652.947	66.316	86.287
Selling and distribution expense	50839.363	88297.589	65753.536	98800.986	35096.625	72941.381
Patent grant	146.195	533.624	229.042	689.681	58.744	266.952
Profit after tax	66695.568	173969.31	113961.83	220802.5	16803.408	78589.939
Return on assets	-510.167	2663.047	-196.006	2546.654	-841.781	2755.974
Herschman Herfindahl Index	1698.426	2266.609	998.792	1433.779	2436.929	2715.91
Concentration Ratio (Top 8 firms)	62.134	26.124	52.247	22.065	72.57	26.12
Total firms	288.827	305.077	388.8	309.458	183.3	263.334

Table 5
Disaggregated Summary Statistics across Different IP intensive and IP neutral industries

Variable	Patent Intensive Industries		Copyright Intensive Industries		Trademark Intensive Industries		IP Neutral Industries	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. dev
Total real Sales	1732201.9	1873358.7	62399.523	78512.967	630622.34	886039.91	3997331.8	5304618.5
Industry IPR index	.582	.226	.448	.244	.511	.272	.652	.284
Net tangible assets	469062.31	636987.8	19116.948	25114.145	325173.08	726580.19	1248044.1	2056895.8
Staff welfare and training expense	10310.11	15202.18	341.369	441.649	1856.321	2342.212	7471.734	8357.969
R&D expenditure	13201.784	24676.602	5.393	12.636	402.822	862.063	3796.52	4042.944
Total liabilities	2062546.4	2644490.1	135550.49	200198.55	1023355	2388507.1	3615820.7	5531452.4
Net patents and copyright	2027.277	5635.429	85.3	104.104	108.562	193.607	85.143	123.664
Selling and distribution expense	71731.05	91830.864	5319.002	7457.545	26845.613	39236.419	127584.04	151080.81
Patent grants	414.49	918.779	0	0	83.16	292.638	0	0
Profit after tax	132611.92	209736.09	6497.178	8345.304	12544.025	65862.171	166043.08	290839.84
Return on assets	361.956	1663.396	-121.141	285.554	-918.191	2924.07	-1231.159	3927.841
Herschman Herfindahl Index	526.907	461.657	4123.869	2922.572	1635.26	2350.631	1592.493	1279.986
Concentration Ratio (Top 8 firms)	46.121	17.846	90.443	12.925	60.972	26.474	66.218	23.648
Total firms	455.898	296.607	31.111	28.08	257.753	284.281	334.857	339.833

Table 6
Disaggregated Summary Statistics of variables across Broad Industry Groups

Variable	Primary		Light Mfg.		Heavy Mfg.		Comp. & IT		Other services		Health and Pharma	
	Obs.	mean	Obs.	mean	Obs.	mean	Obs.	mean	Obs.	mean	Obs.	mean
Sales	7	430127.66	63	563588.48	63	2780292.5	28	946838.74	17	64385.572	7	1183848.9
R&D Int.	7	.002	63	.001	63	.003	28	.001	17	0	7	.027
PAT	7	9467.854	63	20183.114	63	121638.39	28	82639.64	17	1023.476	7	143763.05
ROA	7	-447.31	63	-417.33	63	-780.52	28	-670.79	17	-191.38	7	892.94
IPR	7	.353	63	.601	63	.593	28	.41	17	.447	7	.496

Table 7
Manual fixed effects Sales, R&D and Profit models with broader industry group dummies

DV: $ln\ Sales_t$			DV: $ln\ R\&D_t$			DV: $ln\ ROA_t$		
Variables	**(1)**	**(2)**	**Variables**	**(3)**	**(4)**	**Variables**	**(5)**	**(6)**
	Baseline	**R&D X IPR**		**Baseline**	**R&D X IPR**		**Baseline**	**R&D X IPR**
$ln\ IPR_{t-1}$	0.136	0.288	$ln\ IPR_{t-1}$	0.628	-0.617*	$ln\ IPR_{t-1}$	0.391*	0.0765
	(0.152)	(0.187)		(0.475)	(0.355)		(0.226)	(0.288)
$IPR_{t-1}\ X\ HRD$		-0.523**	$IPR_{t-1}\ X\ HRD$		3.656***	$IPR_{t-1}\ X\ HRD$		1.079*
		(0.203)			(0.676)			(0.594)
$\beta_1 + \beta_2$ (Total Effect)		-0.234	$\beta_1 + \beta_2$ (Total Effect)		3.039***	$\beta_1 + \beta_2$ (Total Effect)		1.1556**
		(0.138)			(0.679)			(0.482)
$ln\ R\&D_{t-1}$	0.0341	0.0754*	$ln\ Sales_{t-1}$	0.549	0.791**	$ln\ R\&D_{t-1}$	0.365***	0.278***
	(0.0479)	(0.0375)		(0.456)	(0.328)		(0.0810)	(0.0862)
$ln\ Stftrainwelf_t$	0.0126	0.00805	$ln\ Totliab_t$	0.112	-0.163	$ln\ Sales_t$	0.486	0.604*
	(0.0351)	(0.0331)		(0.558)	(0.405)		(0.295)	(0.320)
$ln\ tangible_t$	0.0219	0.0262	$ihs\ NetPatcop_t$	0.197**	0.229***	$ln\ HHI_t$	-0.81***	-0.87***
	(0.144)	(0.139)		(0.0753)	(0.0552)		(0.266)	(0.256)
$ln\ Totliab_t$	0.731***	0.720***	$ln\ Totfirms_t$	0.139	-0.0502	$ln\ Totliab_t$	-0.828	-0.858
	(0.118)	(0.115)		(0.315)	(0.203)		(0.547)	(0.532)
$ln\ SDexp_t$	0.334***	0.317***				$ln\ tangible_t$	0.517*	0.494
	(0.0493)	(0.0511)					(0.299)	(0.300)
$ihs\ NetPatcop_t$	-0.0307	-0.0407				$ln\ SDexp_t$	-0.0673	-0.0839
	(0.0378)	(0.0387)					(0.209)	(0.207)
$ln\ Totfirms_t$	-0.0667	-0.0417				$ln\ Stftrainwelf_t$	-0.153	-0.143
	(0.0589)	(0.0576)					(0.158)	(0.156)
						$ihs\ NetPatcop_t$	0.153**	0.173***
							(0.0647)	(0.0596)
						$ln\ Totfirms_t$	-1.34***	-1.44***
							(0.208)	(0.240)
Constant	0.618	0.894	Constant	-5.81***	-6.49***	Constant	11.95***	11.85***
	(0.549)	(0.542)		(1.473)	(0.978)		(3.327)	(3.269)
Industry Groups Dummies	Yes	Yes	Industry Groups Dummies	Yes	Yes	Industry Groups Dummies	Yes	Yes
Year dummies	Yes	Yes	Year dummies	Yes	Yes	Year dummies	Yes	Yes
Observations	185	185	Observations	185	185	Observations	185	185
R-squared	0.966	0.967	R-squared	0.802	0.871	R-squared	0.495	0.507

Clustered robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 8
Two-digit Industry fixed effects Sales, R&D and Profit models

DV: $ln\ Sales_t$			DV: $ln\ R\&D_t$			DV: $ln\ ROA_t$		
Variables	**(1)**	**(2)**	**Variables**	**(3)**	**(4)**	**Variables**	**(5)**	**(6)**
	Baseline	**R&D X IPR**		**Baseline**	**R&D X IPR**		**Baseline**	**R&D X IPR**
$ln\ IPR_{t-1}$	0.184	0.293*	$ln\ IPR_{t-1}$	-0.0201	-0.227	$ln\ IPR_{t-1}$	0.127	-0.0394
	(0.131)	(0.156)		(0.140)	(0.169)		(0.253)	(0.308)
$IPR_{t-1}\ X\ HRD$		-0.520**	$IPR_{t-1}\ X\ HRD$		0.893**	$IPR_{t-1}\ X\ HRD$		0.756
		(0.210)			(0.352)			(0.668)
$ln\ R\&D_{t-1}$	0.0707**	0.0980***	$ln\ R\&D_{t-1}$	0.634***	0.575***	$ln\ R\&D_{t-1}$	0.0894	0.0470
	(0.0336)	(0.0297)		(0.0960)	(0.0906)		(0.120)	(0.113)
$ln\ Stftrainwelf_t$	0.0231	0.0305	$ln\ Sales_{t-1}$	0.0318	0.127	$ln\ Sales_t$	0.587**	0.645**
	(0.0383)	(0.0379)		(0.0919)	(0.105)		(0.265)	(0.259)
$ln\ tangible_t$	0.530	0.518	$ln\ Totliab_t$	-0.0262	-0.128	$ln\ HHI_t$	-0.352	-0.329
	(0.467)	(0.446)		(0.106)	(0.118)		(0.307)	(0.307)
$ln\ Totliab_t$	0.491	0.511	$ihs\ NetPatcop_t$	0.0795*	0.101**	$ln\ Totliab_t$	-0.591	-0.651
	(0.354)	(0.337)		(0.0450)	(0.0480)		(0.816)	(0.810)
$ln\ SDexp_t$	0.341***	0.329***	$ln\ Totfirms_t$	0.0757	0.0980	$ln\ tangible_t$	0.0255	0.0110
	(0.0980)	(0.0956)		(0.125)	(0.113)		(0.705)	(0.703)
$ihs\ NetPatcop_t$	-0.0194	-0.0308				$ln\ SDexp_t$	-0.324**	-0.324**
	(0.0235)	(0.0234)					(0.149)	(0.145)
$ln\ Totfirms_t$	-0.292	-0.303				$ln\ Stftrainwelf_t$	-0.192	-0.206
	(0.265)	(0.256)					(0.148)	(0.148)
						$ihs\ NetPatcop_t$	0.142*	0.160**
							(0.0789)	(0.0735)
						$ln\ Totfirms_t$	-0.907*	-0.862*
							(0.520)	(0.506)
Constant	0.0609	0.242	Constant	0.796	0.426	Constant	8.534*	8.077
	(0.908)	(0.812)		(0.580)	(0.568)		(4.764)	(4.856)
Two-digit Industry Dummies	Yes	Yes	Two-digit Industry Dummies	Yes	Yes	Two-digit Industry Dummies	Yes	Yes
Year dummies	Yes	Yes	Year dummies	Yes	Yes	Year dummies	Yes	Yes
No. of Two-digit Clusters	27	27	No. of Two-digit Clusters	27	27	No. of Two-digit Clusters	27	27
Observations	185	185	Observations	185	185	Observations	185	185
R-squared	0.936	0.939	R-squared	0.826	0.836	R-squared	0.477	0.482

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1*

Table 9
Fixed Effects R&D Model Interacted with Patent, Copyright and Trademark Intensive Industries with Broader Industry Groups as Dummies

Variables	(1) Patent Intensive	(2) Copyright Intensive	(3) Trademark Intensive
$ln\ IPR_{t-1}$	0.160	0.814***	0.781***
	(0.227)	(0.242)	(0.253)
$ln\ Sales_{t-1}$	0.527*	0.358	0.661*
	(0.308)	(0.317)	(0.357)
$ln\ Totliab_t$	0.263	0.243	-0.0183
	(0.340)	(0.337)	(0.380)
$ihs\ NetPatcop_t$	0.148**	0.212***	0.205***
	(0.0653)	(0.0642)	(0.0690)
$ln\ Totfirms_t$	-0.1000	0.00377	0.225
	(0.140)	(0.143)	(0.158)
$IPR_{t-1}\ X\ Patent$	3.206***		
	(0.564)		
$IPR_{t-1}\ X\ Copyright$		-2.840***	
		(1.077)	
$IPR_{t-1}\ X\ Trademark$			-1.692**
			(0.652)
Constant	-6.813***	-4.407***	-5.230***
	(1.216)	(1.400)	(1.207)
Broad Industry dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	185	185	185
R-squared	0.841	0.817	0.811

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10
Manual Fixed Effects Profit (PAT) Model Interacted with Patent, Copyright and Trademark Intensive Industries

Variables	**(1)**	**(2)**	**(3)**
	Patent Intensive	**Copyright Intensive**	**Trademark Intensive**
$ln\ IPR_{t-1}$	-0.785*	-0.793*	-0.0390
	(0.439)	(0.424)	(0.408)
$ln\ R\&D_{t-1}$	0.270	0.520***	0.324**
	(0.180)	(0.160)	(0.144)
$ln\ Sales_t$	2.009***	2.113***	2.196***
	(0.510)	(0.508)	(0.495)
$ln\ HHI_t$	0.430	0.360	0.321
	(0.487)	(0.466)	(0.466)
$ln\ Totliab_t$	-0.440	-0.472	-0.513
	(0.738)	(0.709)	(0.682)
$ln\ tangible_t$	-0.924**	-1.061**	-1.109**
	(0.440)	(0.422)	(0.429)
$ln\ SDexp_t$	-0.0283	-0.0241	-0.0323
	(0.243)	(0.253)	(0.243)
$ln\ Stftrainwelf_t$	0.308*	0.205	0.210
	(0.179)	(0.194)	(0.180)
$ihs\ NetPatcop_t$	0.0571	0.0266	0.101
	(0.111)	(0.114)	(0.111)
$ln\ Totfirms_t$	-1.484***	-1.143***	-1.175***
	(0.451)	(0.434)	(0.438)
$IPR_{t-1}\ X\ Patent$	2.449**		
	(1.017)		
$IPR_{t-1}\ X\ Copyright$		4.658***	
		(1.411)	
$IPR_{t-1}\ X\ Trademark$			-3.837***
			(1.183)
Constant	-3.703	-4.132	-1.379
	(5.556)	(4.949)	(4.981)
Broad Industry dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	185	185	185
R-squared	0.495	0.510	0.516

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 11
Fixed Effects models of Sales interacted with broad industry groups

Variables	(1) Primary	(2) Light mfg.	(3) Heavy mfg.	(4) Comp & IT	(5) Other services	(6) Health & Pharma
$ln\ IPR_{t-1}$	0.185	0.161	0.277	0.314*	0.0720	0.184
	(0.136)	(0.119)	(0.191)	(0.156)	(0.0901)	(0.134)
$ln\ R\&D_{t-1}$	0.0705**	0.0712**	0.0786**	0.0502	0.0870***	0.0708**
	(0.0340)	(0.0332)	(0.0319)	(0.0351)	(0.0278)	(0.0337)
$ln\ Stftrainwelf_t$	0.0233	0.0234	0.0188	0.0282	-0.00612	0.0231
	(0.0394)	(0.0388)	(0.0355)	(0.0362)	(0.0272)	(0.0379)
$ln\ tangible_t$	0.530	0.534	0.520	0.505	0.293	0.530
	(0.469)	(0.472)	(0.451)	(0.419)	(0.310)	(0.468)
$ln\ Totliab_t$	0.491	0.490	0.509	0.507	0.684***	0.491
	(0.353)	(0.354)	(0.339)	(0.327)	(0.221)	(0.355)
$ln\ SDexp_t$	0.341***	0.343***	0.328***	0.372***	0.298***	0.341***
	(0.0983)	(0.0985)	(0.0984)	(0.0949)	(0.0783)	(0.0983)
$ihs\ NetPatcop_t$	-0.0195	-0.0222	-0.0254	-0.0134	0.00814	-0.0195
	(0.0237)	(0.0269)	(0.0251)	(0.0202)	(0.0180)	(0.0247)
$ln\ Totfirms_t$	-0.294	-0.292	-0.296	-0.249	-0.351	-0.292
	(0.277)	(0.265)	(0.272)	(0.222)	(0.246)	(0.265)
$IPR_{t-1}\ X\ Primary$	-0.126					
	(1.239)					
$IPR_{t-1}\ X\ lightmfg$		0.162				
		(0.408)				
$IPR_{t-1}\ X\ Heavymfg$			-0.476			
			(0.397)			
$IPR_{t-1}\ X\ Comp$				-2.558**		
				(0.998)		
$IPR_{t-1}\ X\ otrservice$					5.477***	
					(0.905)	
$IPR_{t-1}\ X\ Pharma$						-0.0187
						(0.461)
Constant	0.0641	-0.0461	0.223	0.0287	0.250	0.0613
	(0.898)	(1.033)	(0.813)	(0.900)	(0.667)	(0.904)
Two-digit Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185	185	185	185	185	185
R-squared	0.936	0.936	0.937	0.942	0.952	0.936

Clustered standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table 12
Fixed Effect model of R&D interacted with broad industry groups

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Primary	Light mfg.	Heavy mfg.	Comp & IT	Other Services	Health & Pharma
$ln\ IPR_{t-1}$	-0.359	-0.336	-0.674*	-0.260	-0.337	-0.417
	(0.295)	(0.238)	(0.390)	(0.311)	(0.284)	(0.288)
$ln\ Sales_{t-1}$	0.425	0.413	0.469	0.359	0.582*	0.418
	(0.288)	(0.279)	(0.278)	(0.312)	(0.308)	(0.284)
$ln\ Totliab_t$	-0.298	-0.336	-0.378	-0.245	-0.468	-0.323
	(0.314)	(0.328)	(0.321)	(0.328)	(0.311)	(0.312)
$ihs\ NetPatcop_t$	0.133*	0.146**	0.154**	0.142*	0.116	0.142*
	(0.0696)	(0.0634)	(0.0659)	(0.0705)	(0.0726)	(0.0727)
$ln\ Totfirms_t$	-0.178	-0.0908	-0.0514	-0.0376	-0.0164	-0.0891
	(0.400)	(0.405)	(0.374)	(0.383)	(0.409)	(0.399)
$IPR_{t-1}\ X\ primary$	-6.615**					
	(2.540)					
$IPR_{t-1}\ X\ lightmfg$		-0.499				
		(1.239)				
$IPR_{t-1}\ X\ heavymfg$			1.441*			
			(0.756)			
$IPR_{t-1}\ X\ Comp$				-2.419		
				(2.020)		
$IPR_{t-1}\ X\ otrservice$					-3.571	
					(2.213)	
$IPR_{t-1}\ X\ Pharma$						2.076**
						(0.933)
Constant	1.993	2.211	1.197	1.806	1.448	1.802
	(1.544)	(1.455)	(1.463)	(1.506)	(1.771)	(1.495)
Two-digit Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185	185	185	185	185	185
R-squared	0.649	0.643	0.653	0.649	0.651	0.643
No. of two-digit clusters	27	27	27	27	27	27

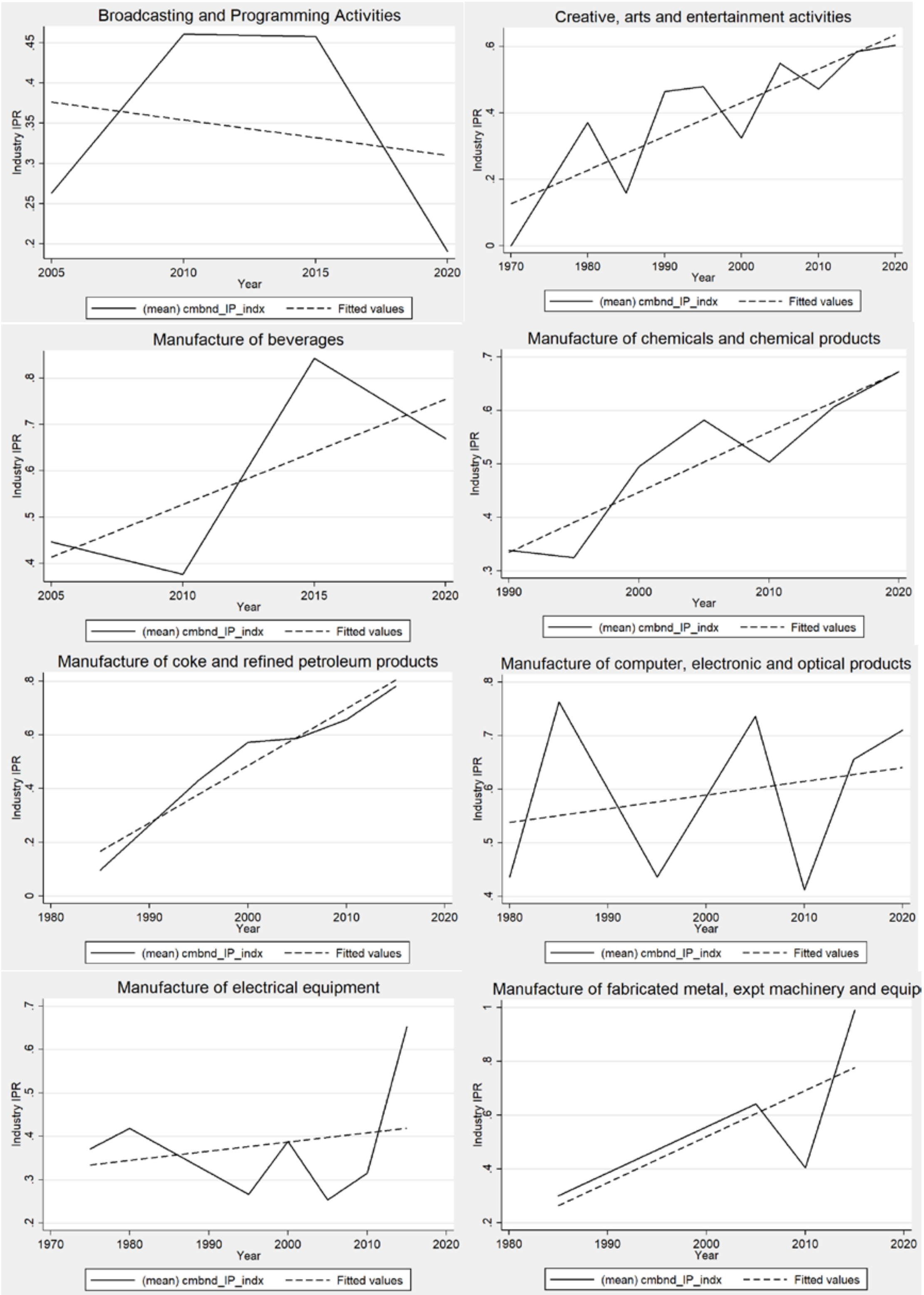
Clustered standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 13
Fixed Effects models for Profit (ROA) interacted with broad industry groups

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Primary	Light mfg.	Heavy Mfg.	Comp & IT	Other Services	Health & Pharma
$ln\ IPR_{t-1}$	0.115	-0.258	0.0741	0.178	0.138	0.0569
	(0.251)	(0.216)	(0.364)	(0.277)	(0.237)	(0.249)
$ln\ R\&D_{t-1}$	0.0315	0.0467	0.0395	0.0309	0.0146	0.0374
	(0.116)	(0.122)	(0.117)	(0.120)	(0.114)	(0.117)
$ln\ Sales_t$	0.562**	0.558**	0.577**	0.520*	0.803**	0.578**
	(0.268)	(0.267)	(0.262)	(0.274)	(0.380)	(0.266)
$ln\ HHI_{t-1}$	-0.299	-0.386	-0.418	-0.434	-0.428	-0.416
	(0.339)	(0.316)	(0.325)	(0.331)	(0.324)	(0.328)
$ln\ Totliab_t$	-0.507	-0.529	-0.532	-0.492	-0.816	-0.532
	(0.878)	(0.834)	(0.887)	(0.882)	(0.971)	(0.879)
$ln\ Tangible_t$	-0.0219	0.0363	-0.0386	-0.0232	0.0573	-0.0403
	(0.731)	(0.708)	(0.741)	(0.729)	(0.752)	(0.733)
$ln\ SDexp_t$	-0.336**	-0.306**	-0.342**	-0.303**	-0.380**	-0.340**
	(0.158)	(0.148)	(0.158)	(0.147)	(0.185)	(0.156)
$ihs\ Netpatcop_t$	0.149*	0.108	0.147*	0.149*	0.126*	0.155*
	(0.0799)	(0.0874)	(0.0800)	(0.0798)	(0.0721)	(0.0847)
$ln\ Totfirms_t$	-1.045**	-0.997**	-1.009*	-1.002*	-0.888	-1.008*
	(0.493)	(0.481)	(0.502)	(0.504)	(0.543)	(0.502)
$IPR_{t-1}\ X\ primary$	-6.517**					
	(2.397)					
$IPR_{t-1}\ X\ lightmfg$		2.426**				
		(1.153)				
$IPR_{t-1}\ X\ heavymfg$			0.00314			
			(0.886)			
$IPR_{t-1}\ X\ Comp$				-1.731		
				(1.371)		
$IPR_{t-1}\ X\ otrservice$					-4.795	
					(6.065)	
$IPR_{t-1}\ X\ Pharma$						3.084*
						(1.670)
Constant	8.665*	7.672*	9.492**	9.603**	9.354**	9.389**
	(4.355)	(4.217)	(4.478)	(4.333)	(4.440)	(4.425)
Two-digit Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185	185	185	185	185	185
R-squared	0.472	0.481	0.469	0.471	0.477	0.470
Number of clusters	27	27	27	27	27	27

Clustered standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Figure 1
Trends in the IPR Implementation Index Across a Selected Group of Industries Over Time



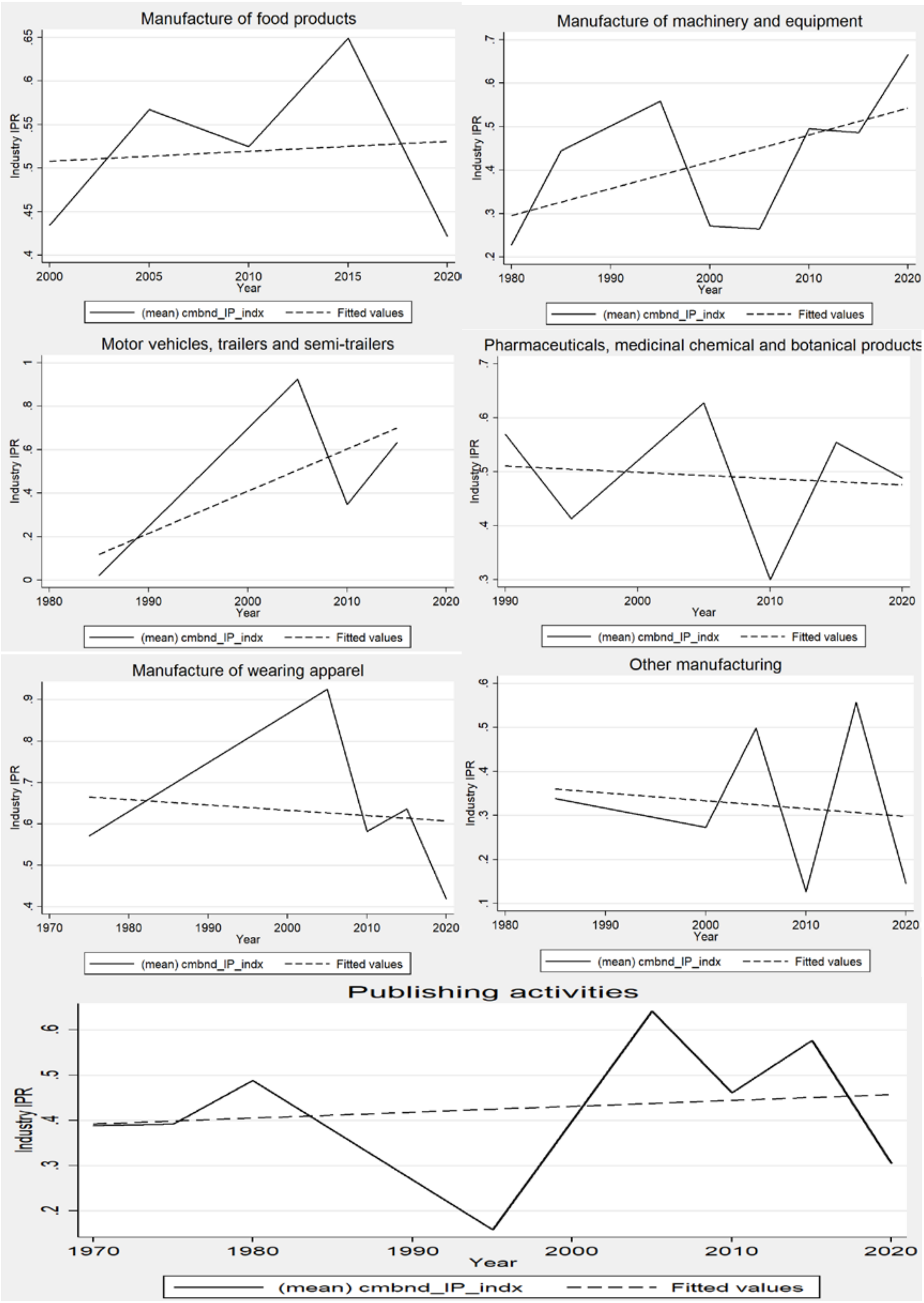
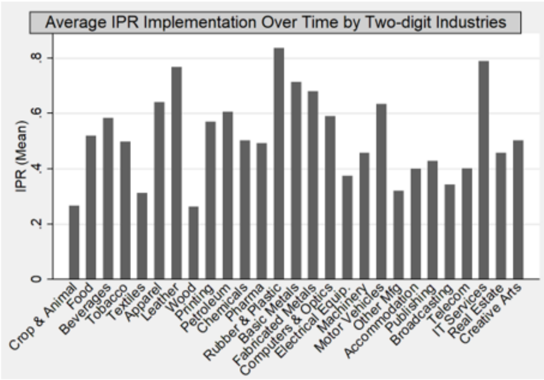
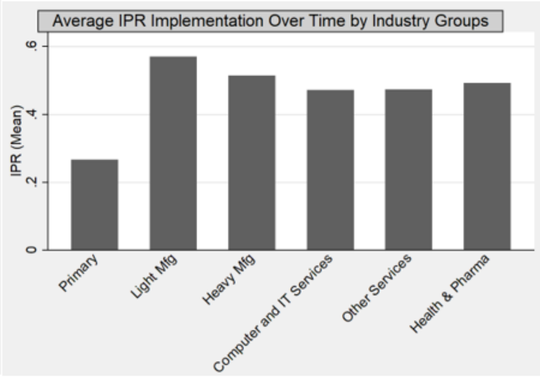

Manufacture of food products
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Manufacture of machinery and equipment
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Motor vehicles, trailers and semi-trailers
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Pharmaceuticals, medicinal chemical and botanical products
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Manufacture of wearing apparel
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Other manufacturing
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values
Publishing activities
Industry IPR
Year
(mean) cmbnd_IP_indx
Fitted values

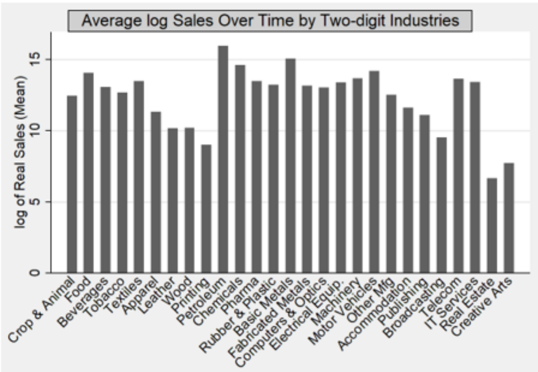
Figure 2
Average of IPR and Sales Across Two-digit and Broad Industry Groups



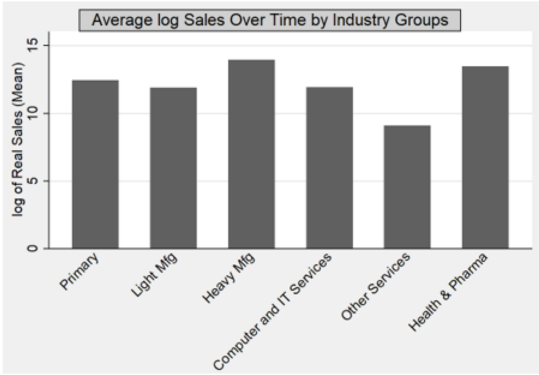
(a)



(b)



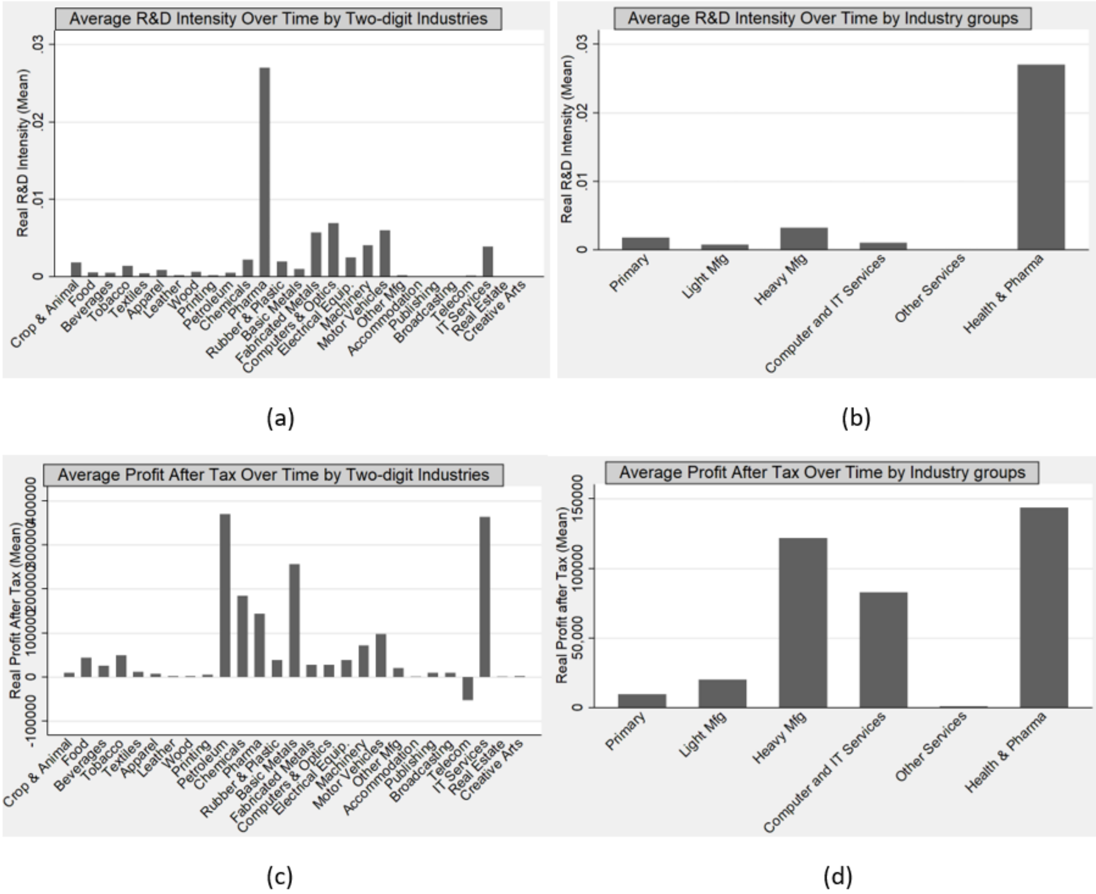
(c)



(d)

Source: IPR is the industry-wise de facto IPR index and sales data is taken from CMIE Prowess

Figure 3
Average of R&D and Profit Across Two-digit and Broad Industry Groups



(a) (b) (c) (d)

Source: R&D and profit data is taken from CMIE Prowess