INSIDER TRADING AND INNOVATION

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Abstract

This paper assesses whether the enforcement of insider trading laws increases or decreases patent-based measures of technological innovation. Based on about 75,000 industry-country-year observations across 94 economies from 1976 to 2006, we find evidence consistent with the view that enforcing insider trading laws spurs innovation—as measured by patent intensity, scope, impact, generality, and originality—after controlling for country-year and industry-year fixed effects. Consistent with theories that insider trading slows innovation by impeding the valuation of innovative activities, the relationship between enforcing insider trading laws and innovation is much larger in industries that are naturally innovative and opaque, where we use the U.S. to benchmark industries.

Key Words: Insider Trading; Financial Regulation; Intellectual Property Rights; Patents
JEL Classifications: G14; G18; O30; F63

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1. Introduction

Two literatures motivate the question: Does the enforcement of insider trading laws accelerate or slow technological innovation? The law and finance literature shows that legal systems that protect outside investors from corporate insiders boost the functioning of financial markets (e.g., La Porta et al. 1997, 1998, 2002, 2006, and Djankov et al. 2008). In turn, the finance and growth literature emphasizes that the functioning of financial systems shapes economic growth (e.g., King and Levine 1993a,b, Levine and Zervos 1998, Rajan and Zingales 1998, Beck et al. 2000, 2010). What these literatures have not yet addressed is whether legal systems that protect outside investors from insider trading—trading by corporate officials, major shareholders, or others based on material non-public information—influence a crucial source of economic growth: technological innovation.

Theory offers differing views on how insider trading influences innovation. The valuation view stresses that restricting insider trading enhances the valuation of innovative endeavors and thereby accelerates technological innovation. Specifically, technological innovations are often risky and difficult to assess (e.g., Holmstrom 1989, Allen and Gale 1999), so that improving valuations can enhance investment in innovative activities (Merton 1987). By reducing the ability of corporate insiders to exploit other investors through insider trading, enforcing insider trading laws can encourage those investors to devote more resources to valuing firms, as modeled by Fishman and Hagerty (1992) and shown empirically by Bushman et al. (2005), Fernandes and Ferreira (2009), and Jayaraman (2012), improving valuations, and spurring technological innovation.[1]

The liquidity view stresses that restricting insider trading can affect innovation by altering stock market liquidity. By reducing concerns that insiders will exploit other investors, Bhattacharya and Daouk (2002) find that enforcing insider trading tends to boost market participation and liquidity. On the one hand, greater liquidity can strengthen the valuation effect. More liquid markets make it less costly for investors who have acquired

[1] There is considerable debate concerning the private and social costs and benefits of insider trading, as exemplified by the work of Leland (1992), Khanna et al (1994), and DeMarzo, Fishman, and Hagerty (1998).

information to profit by trading in public markets (Kyle 1984), which encourages investors to devote more effort to enhancing the valuation of innovative activities (Holmstrom and Tirole 1993). Furthermore, liquid markets that quickly aggregate and reveal information can facilitate the governance of firms, including those engaged in innovative endeavors (McConnell et al. 1982 and Jensen and Murphy 1990).

On the other hand, more liquid markets can impede innovation. Grossman and Stiglitz (1980) emphasize that when liquid stock markets immediately reveal information to the public, this reduces incentives for investors to expend private resources acquiring information. Thus, if restricting insider trading boosts liquidity, which in turn discourages information production and harms corporate valuations, the increase in liquidity can impede efficient investment in innovative activities. Furthermore, greater liquidity can hurt innovation by weakening corporate governance. Bhide (1993) and Chordia et al. (2005) argue that greater market liquidity can discourage investors from engaging in the costly process of governing firms by giving them a low-cost exit mechanism. In addition, Stein (1989) explains that efficient, liquid markets can induce managers to behave myopically and sacrifice long-term investments, such as those in innovation, to meet short-term performance targets. Thus, the valuation and liquidity views offer differing perspectives on the impact of the enforcement of insider trading laws on innovation.[2]

In this paper, we provide the first assessment of whether the enforcement of insider trading laws increases the rate of technological innovation. To do this, we obtain information on patenting activities for industries (two-digit SIC level) in 94 countries over the years starting in 1976 and running through 2006 from the Worldwide Patent Statistical Database (PATSTAT). We compile a large and comprehensive sample of 76,321 industry-country-year observations. We obtain information on the enforcement of insider trading laws from

[2] There might be other mechanisms through which insider trading influences innovation. For example, enforcing insider trading can reduce the returns to being a corporate insider. Thus, the enforcement of insider trading laws could induce corporate insiders to have the firm invest in higher-risk activities, including innovation, to compensate for the reduced ability to profit from insider trading. Thus, the valuation and liquidity views are not meant as an exhaustive list of theoretically feasible mechanisms linking insider trading and innovation. They are meant to help motivate and frame our empirical examination.

Bhattacharya and Daouk (2002) and evaluate whether changes in the enforcement of insider trading laws influence patent-based measures of innovation. We differentiate the effects of changes in the enforcement of insider trading laws on innovation by industry since, as we describe below, theory suggests that the impact of insider trading laws will differ by the underlying characteristics of industries. In the reported regressions, we follow the literature (e.g., Rajan and Zingales 1998) and omit the United States because we use U.S. data to categorize industries; however, the analyses hold when including the U.S.

We examine the enforcement of insider trading laws. Bhattacharya and Daouk (2002) find that the first time that a country prosecutes a violator of its insider trading laws—not the mere existence of such laws— influences markets. Consequently, we define our insider trading enforcement indicator as equal to zero if the country has not yet prosecuted a violator of those laws and equal to one after the first prosecution.

We examine five patent-based proxies for technological innovation, all measured at the industry-country-year level. To gauge intensity, we use the number of patents. To measure the scope of innovative activities, we examine the number of patenting entities using the procedure developed by Acharya and Subramanian (2009). We also use three measures of the impact, generality, and originality of each patent from Hall et al. (2001). To proxy for impact, we use the number of citations to patents and adjust for the age of the patent. To measure the generality of a patent within one technology class, we use the degree to which other technology classes cite the patent. Finally, to measure originality—the degree to which the patent is based on innovations outside of its own area of investigation, we use a measure of the degree to which the patent cites innovations in other technology classes.

We conduct an initial assessment of the relationship between the patent-based proxies of innovation and the enforcement of insider trading laws using a difference-in-differences specification. In the regressions, the dependent variable is one of the five patent-based proxies of innovation. The explanatory variable of focus is the enforcement of insider trading laws indicator. The regressions also include country, industry, and year fixed effects along with an assortment of time-varying country and industry characteristics.

We find that the enforcement of insider trading laws is associated with a material and statistically significant increase in each of the five proxies of innovation. For example, the number of patents rises, on average, 26% after a country first enforces its insider trading laws and the impact of innovation, as measured by citation counts, increases by 37%. Furthermore, we find no evidence of reverse causality: Neither the patent-based measures of innovation nor trends in those measures predict the timing of when a country starts enforcing its insider trading laws.

Next, we build on these initial analyses to better identify the mechanisms linking the enforcement of insider trading laws and technological innovation, which also helps address several interpretational challenges associated with the simple difference-in-differences specification. In particular, unobserved time-varying country and industry characteristics might spur both the uptick in innovation and the enforcement of insider trading laws.

Our identification strategy is to assess the cross-industry patterns of changes in innovation after a country first enforces its insider trading laws and evaluate whether these patterns are consistent with the predictions of some theories and inconsistent with others. In particular, both the valuation and liquidity views make predictions about the cross-industry impact of insider trading on innovation. In these industry-level analyses, we control for country-year and industry-year fixed effects. Thus, we condition out all time-varying country factors that might be changing at the same time as each country first enforces its insider trading laws and we also control for changing industry characteristics that confound the ability to draw sharp inferences about the relationship between insider trading and innovation. Thus, by focusing on changes in the cross-industry patterns of innovation, these analyses provide cleaner insights into the relationship between insider trading and innovation.

We differentiate industries along three theoretically-motivate dimensions. First, we distinguish among industries by their "natural rate" of innovation. If insider trading curtails innovation by dissuading potential investors from expending resources valuing innovative activities, then enforcement of insider trading laws should have a particularly pronounced effect on innovation in naturally innovative industries—industries that would have experienced rapid innovation if insider trading had not impeded accurate valuations. Given that the United States is a highly innovative economy with well-developed securities markets that was also the first country to prosecute a violator of its insider trading laws, we use it as a benchmark to compute the natural rate of innovation for each industry. Using several measures of the natural rate of innovation based on U.S. industries, we evaluate whether innovative industries experience a bigger jump in innovation after a country starts enforcing its insider trading laws.

Second, we differentiate industries by opacity. If insider trading discourages innovation by impeding market valuations, then the enforcement of insider trading laws is likely to exert an especially large positive impact on innovation in industries with a high degree of informational asymmetries between insiders and potential outside investors. Put differently, there is less of role for greater enforcement of insider trading limits to influence innovation through the valuation channel if the pre-reform information gap is small. We use several proxies of opacity across industries, again using the U.S. as the benchmark economy to define each industry's "natural" opacity. We then test whether naturally opaque industries experience a larger increase in innovation rates after a country first prosecutes somebody for violating its insider trading laws.

Third, we differentiate industries by stock market liquidity. If (a) some industries naturally have more liquid shares than other industries and (b) insider trading keeps liquidity below this naturally high level, then the liquidity view implies that the enforcement of insider trading laws will have a particularly pronounced impact on naturally liquid industries. Again, using U.S. industries to form benchmarks, we test whether industries with "naturally" liquid shares experience a large change in innovation when a country starts enforcing its insider trading laws.

The results from the industry-level analyses are consistent with the valuation view of how insider trading shapes innovation, but provide no direct support for the liquidity view. First, each of the five patent-based measures of innovation rises much more in naturally innovative industries. These results hold when measuring naturally innovative industries in several ways in which we use the U.S. to benchmark industries. For example, the number of patents jumps 50% more in industries that have above the median level of patenting activity in the U.S. than those industries with below the median values after a country starts enforcing its insider trading laws. Second, industries that are naturally opaque experience a bigger increase in all of the patent-based measures of innovation after a country first enforces its insider trading laws. For example, in industries with above the median levels of intangible assets in the U.S., the patent-based measures of innovation increase 25% more than in industries with naturally lower levels of intangible assets. In contrast, we find no evidence that the enforcement of insider trading laws disproportionately affects innovative activity in naturally more liquid industries.

We further extend these analyses by examining one channel through which insider trading might affect innovation. The valuation view suggests that insider trading reduces the incentives of potential investors to expend resources researching innovative activities, which hinders market valuations and impedes the ability of innovative firms to issue equities. Thus, we directly gauge whether firms in naturally innovative industries disproportionately increase their issuances of equities relative to other industries when countries start enforcing insider laws.

Consistent with the valuation view, we find that initial public offering (IPO), seasonal equity offering (SEO), and total equity offerings increase much more in naturally innovative industries. In particular, the value of equity issuances increases 25% more in naturally innovative industries than it rises in other industries after a country starts enforcing its insider trading laws. The results are consistent with the valuation channel.

This paper contributes to recent work on finance and technological innovation. Hsu et al. (2014) find that large equity markets—as measured by market capitalization—spur patent production, while Fang et al. (2014) find that increases in market liquidity slow the rate at which firms file for patents. Rather than examining the relationship between the number of patents and measures of stock market size and liquidity, we examine what happens to patent intensity, scope, impact, generality, and originally across industries after countries change one particular policy lever—the enforcement of insider trading laws. Other work focuses on the impact of overall financial system development on aggregate rates of economic growth and innovation (e.g., Levine (1991), King and Levine (1993a,b), Levine (2005), Amore et al (2013), Chava et al (2013), Acharya and Xu (2015), and Laeven et al (2015)). Our work adds to this research by examining whether the enforcement of insider trading laws, which shapes overall financial development (Bhattacharya and Daouk 2002, 2009), also shapes changes in the cross-industry patterns of technological innovation in ways that are consistent with particular theories of how financial markets affect rates of innovation and economic growth. In research that is close in spirit to ours, Acharya and Subramanian (2009) examine how bankruptcy codes affect innovation. We, in turn, examine how the enforcement of insider trading laws shape innovation. Manso (2011) and Ferreira et al. (2014) develop models examining how managerial contracts and ownership structure shape incentives for corporations to innovate. Although we do not assess the specific predictions emerging from these models, our findings are consistent with the view that protecting potential investors from insider trading can shape the incentives facing corporate executives with material ramifications on the rate of technological innovation.

The rest of the paper proceeds as follows. Section 2 discusses the data, while section 3 presents the empirical strategies and validity tests. Section 4 provides the main results and robustness checks, and section 5 examines insider trading and equity issuances. Section 6 concludes.

2. Data

To assess the relationship between the enforcement of insider trading laws and innovation, we use data on the enforcement of insider trading laws and patent-based measures of innovation and employ a difference-in-differences methodology. In this section, we describe the international data on the enforcement of insider trading laws and patents. When we present the regression results below, we define other data used in the analyses. *Table 1* provides summary statistics on key variables and Appendix *Table A1* provides detailed information on the data sources and variable construction.

2.1. Enforcement of insider trading laws

Bhattacharya and Daouk (2002) compile data on the enforcement of insider trading laws for 103 economies. They obtain this data by contacting stock exchanges and asking (a) whether they had insider trading laws and, if yes, in what year were they first enacted and (b) whether there had been prosecutions, successful or unsuccessful, under these laws and, if yes, in what year was the first prosecution. We use the enforcement, rather than the existence, of insider trading laws because Bhattacharya et al. (2000) note that the existence of insider trading laws without the enforcement of them does not deter insider trading. Furthermore, following Bhattacharya and Daouk (2002), Denis and Xu (2013), and others, we use the first time that a country's authorities enforce insider trading laws because the initial enforcement (a) represents a shift of legal regime from a non-prosecution to a prosecution regime and (b) signals a discrete jump in the probability of future prosecutions. Based on the information in Appendix Table A2, 82 out of the 94 countries with complete data had insider trading laws on their books by 2002, but only 36 of those 82 economies had enforced those laws at any point before 2002. As a point of reference, the United States first enacted laws prohibiting insider trading in 1934 and first enforced those laws in 1961.

Enforce equals one in the years after a country first enforces its insider trading laws, and otherwise equals zero. For those years in which a country does not have insider trading laws, *Enforce* equals zero. *Enforce* equals zero in the year of the first enforcement, but the results are robust to setting it to one instead.

2.2. Patents

The Worldwide Patent Statistical Database (PATSTAT) provides data on more than 80 million patent applications filed in over 100 patent offices around the world. It contains basic bibliographic information on patents, including the identity number of the application and granted patent, the date of the patent application, the date of patent grant, the track record of patent citations, information on the patent assignees (i.e., the owner of the patent), and the technological “section”, “class”, and “subclass” to which each patent belongs (i.e., the International Patent Classification (IPC)).[3] IPCs assigned to a patent can be inventive or non-inventive. All patents have at least one inventive IPC. We only use inventive IPCs for classifying a patent’s technological section, class, and subclass. Furthermore, if the patent authority designates an inventive IPC as secondary (“L” in the ipc_position of the PATSTAT), we remove that IPC from further consideration. This leaves only inventive IPCs that the patent authority designates as primary (“F” in the ipc_position of the PATSTAT) or that the patent authority does not designate as either primary or secondary, i.e., undesignated IPCs. In no case does a patent authority designate a patent as having two primary IPCs. In the few cases in which a patent has multiple inventive undesignated IPCs, we follow a simple procedure for classifying the patent.[4]

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[3] For example, consider a typical IPC “A61K 36/815”. The first character identifies the IPC “section”, which in this example is “A”. There are eight sections in total (from A to H). The next two characters (“61” in this example) give the IPC “class”; the next character, “K”, provides the “subclass”; the next two characters (“36”) give the “main group”, while the last three characters (“815”) give the sub-group. Not all patent authorities provide IPCs at the main-group and sub-group levels, so we use the section, class, and subclass when referring to an IPC. With respect to these technological classifications, there are about 600 IPC subclasses.

[4] In our dataset, 19% of patents have multiple inventive IPCs (in which the patent authority designates the IPC as either primary or does not give it a designation); where 6% have both a primary inventive IPC and at least one undesignated IPC; and 13% have no primary IPC and multiple undesignated IPCs. In cases with multiple inventive IPCs, we do the following. First, we assign equal weight to each IPC subclass. That is, if a patent has two IPC subclasses, we count it as 0.5 in each subclass. From a patent’s IPC subclasses, we choose a unique IPC section. We simply choose the first one based on the alphabetical ordering of the IPC sections.

Critically, PATSTAT provides an identifier of each distinct "patent family," which includes all of the patents linked to a particular invention since some inventions are patented in multiple patent offices. With this patent family identifier, we can identify the first time an invention is patented and we call this the "original patent." PATSTAT is updated biannually and we use the 2015 spring release, which covers patent information as of the end of the fifth week of 2015.

We restrict the PATSTAT sample as follows. We only include patents filed with and eventually granted by the EPO or one of the patent offices in the 34 member countries of the Organization for Economic Co-operation and Development (OECD) to ensure comparability across jurisdictions of intellectual property rights. We further restrict the sample to non-U.S. countries because we use the United States as the benchmark economy when characterizing industry traits for all countries (Rajan and Zingales 1998). To further mitigate potential problems with using U.S. industries as benchmarks, we only include a country in the sample if at least one entity in the country has applied for and received a patent for its invention from the United States Patent and Trademark Office (USPTO) within our sample period because industries in these economies are presumably more comparable with those in the United States. This restriction excludes Zambia, Namibia, Botswana, and Mongolia. The results, however, are robust to including these countries or the United States in the regression analyses. Finally, since we use data from the United Nations Commodity Trade (UN Comtrade) Statistics Database in our regression analyses, we exclude economies that UN Comtrade does not cover (Taiwan and Yugoslavia). Throughout the analyses, we follow the patent literature and focus on utility patents.[5]

After employing these restrictions and merging the patent data with the data on the enforcement of insider trading laws, we have a sample of 94 economies between 1976 and 2006. The exact number of countries in each year varies because some countries do not file for patents in some years.

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[5] In addition to utility patents, the PATSTAT also includes two other minor patent categories: utility models and design patents. As with the NBER patent database, Hall et al. (2001), and consistent with U.S. patent law, we only include utility patents.

Following the patent literature, we date patents using the application year of patents that are eventually granted. The literature uses the application year, rather than the actual year in which the patent is granted, because the application year is closer to the date of the innovation (Griliches et al. 1987) and because the application year avoids varying delays between the application and grant year (Hall et al. 2001; Acharya and Subramanian 2009). Moreover, we use the original patent—the first patent on an invention—when defining the date, the technological section and subclass(es), the country of the invention, etc. That is, if the same underlying invention has multiple patents, i.e., the patents are part of a patent family, we choose the patent with the earliest grant date and call this the original patent. We then use the application year of this original patent to (a) date the invention, (b) define the technological section and subclass(es) of the invention (i.e., its IPC(s)), and (c) record the nationality of its primary assignee (i.e., owner) and the country of the invention.

When computing measures of innovation based on citations, we avoid double counting by different patents within a patent family, by examining citations at the patent family level. Thus, if another patent cites multiple patents in different patenting offices on the single invention underlying a patent family "A," we count this as one citation. In this way, we focus on citations by inventions to inventions regardless of where and in how many offices the inventions are patented.

Since we conduct our analyses at the industry-level and merge different data sources, we must reconcile the different industrial classifications used by the PATSTAT and the other data sources. In the same spirit as Hsu et al. (2014), we convert the PATSTAT IPCs into two-digit Standard Industrial Classifications (SICs).[6]

We construct five measures of innovative activities for each industry-country-year.

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[6] We first follow the mapping scheme provided by Lybbert and Zolas (2012) for converting IPCs into International Standard Industrial Classifications (ISICs). The World Intellectual Property Office (WIPO) provides the Lybbert and Zolas (2012) mapping scheme at: http://www.wipo.int/econ_stat/en/economics/publications.html. We then convert the ISIC to SICs using the concordance scheme from the United Nations Statistical Division, which is detailed at: http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1.

Patent Count in industry *i*, in country *c*, in year *t* equals the natural logarithm of one plus the total number of eventually-granted patent applications belonging to industry *i* that are filed with the patent offices in one of the 34 OECD countries and/or the EPO in year *t* by applicants from country *c*. As emphasized above, we do everything at the invention—patent family—level and then convert the PATSTAT IPCs to two-digit SICs.

Patent Entities equals the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. Similar to *Patent Count*, *Patent Entities* is also constructed at the IPC subclass level and then converted to the two-digit SIC level. Following Acharya and Subramanian (2009), we include *Patent Entities* since it accounts for the scope of participation in innovative activities. While *Patent Count* and *Patent Entities* measure the intensity and scope of innovative activities, respectively, they do not measure the comparative impact of different patents on future innovation (Acharya and Subramanian 2009; Hsu et al. 2014). Thus, we also use measures based on citations.

Citation equals the natural logarithm of one plus the total number of citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. Thus, if a patent cites two patents on the same invention filed in different patent offices, we only count this as one citation. Similarly, if two patents in the same patent family each cites an invention, we only count this as one citation. As emphasized above, we seek to measure citations by inventions of other inventions and not double count such citations because of an invention being patented in multiple offices. As an invention—a patent family—may continue to receive citations for years beyond 2014, the last full year covered by the PATSTAT, we adjust for truncation bias using a method developed by Hall et al. (2001, 2005).[7] Then, we sum the citation counts over all patent families within each IPC subclass and convert this to the two-digit SIC level for each industry *i*, in country *c*, and in year *t*.

[7] More specifically, for patents granted in and before 1985 (when at least 30-years of actual citations can be observed by the end of 2014), we use the actual citations recorded in the PATSTAT. For patents granted after 1985, we implement the following four-step process to adjust for truncation bias.
(1) Based on each cohort of granted patents for which we have 30 years of actual citation data (e.g., patents granted in 1985 or earlier), we compute for each IPC section (*K*), the share of citations in each year (*L*) since the patents were granted, where the share is relative to the total number of citations received over the 30 years since

Generality is a measure of the degree to which patents by each particular industry in a country *are cited by* patents in other types of technologies. Thus, a high generality score suggests that the invention is applicable to a wide array of inventive activities. We construct *Generality* as follows. We first compute a patent's generality value as one minus the Herfindahl Index of the IPC sections of patents citing it. This provides information on the degree to which a patent is cited by different technologies, i.e., sections other than the IPC section of the patent itself. We then sum the generality scores of all patents within each IPC subclass, in each country, and each year. Finally, we convert the resultant values to SIC industries using the method describe above and take the natural logarithm of one plus the original value to obtain an overall *Generality* measurement at the industry-country-year level.

Originality is a measure of the degree to which patents by each particular industry in a country *cite* patents in other types of technologies. Larger values of *Originality* indicate that patents in that industry build on innovations from a wider array of technologies, i.e., the patents in that industry do not simply build on a single line of inventions. We construct *Originality* as follows. We first compute a patent's originality value as one minus the Herfindahl Index of the IPC sections of patents that it cites. We then sum the originality

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the patents were granted. We refer to this share, for each IPC section in each year, as P_L^K, where $L = 0,1,\dots,29,$ and $\sum_{L=0}^{29} P_L^K = 1$ for each *K*. The year of the grant corresponds to year zero.

(2) We calculate the cumulative share of citations for section *K* from year zero to year *L*. We refer to this cumulative share for each IPC section *K* for each year *L* as S_L^K, where $S_L^K = \sum_{\tau=0}^{L} P_\tau^K$, $L = 0,1,\dots,29,$ and $S_{L=29}^K = 1$.

(3) After completing steps (1) and (2) for all patents granted before 1985, where 1985 is the last cohort in which we have 30 years of actual citation data, we compute the average cumulative share for each S_L^K over the ten cohorts (1976-1985) to obtain a series of estimates $\bar{S}_L^K$. We use the average cumulative share $\bar{S}_L^K$ as the estimated share of citations that a patent receives if it belongs to section *K* and was granted *L* years before 2014. Thus, $\bar{S}_L^K$ equals 1 for patents granted in and before 1985.

(4) We then apply the series of average cumulative share, $\bar{S}_{L=0}^K$ to $\bar{S}_{L=28}^K$, to patents granted after 1985. For instance, for a patent in section *K* and granted in 1986, we observe citations from $L=0$ to $L=28$ (i.e., for 29 years till the end of 2014). According to the calculations in (3), this accounts for the share $\bar{S}_{L=28}^K$ of total citations of the patent in section *K* that was granted in 1986 over a 30-year lifetime. We then multiply the actual citations of the patent in section K summed over the 1986-2014 period by the weighting factor of $1/\bar{S}_{L=28}^K$ to compute the adjusted citations for the patent in sections *K* and cohort 1986. As another example, consider a patent in section *K* and granted in 2006. We observe actual citations from $L=0$ to $L=8$ (i.e., for 9 years till the end of 2014). According to our calculations, these actual citations account for the share $\bar{S}_{L=8}^K$ of total citations of the patent in section *K* that was granted in 2006 over a 30-year lifetime. In this example, then, we multiply the actual sum of citations over the period 2006-2014 by the weighting factor of $1/\bar{S}_{L=8}^K$ to compute the adjusted total citations for the patent in section *K* and cohort 2006.

values of all patents within each IPC subclass, in each country, in each year. Finally, we map this IPC-based indicator to SIC industries and take the natural logarithm of one plus the original value to obtain an overall *Originality* measurement at the industry-country-year level.[8]

We also construct and use two variants of these measures. Specifically, Patent Count*, Patent Entities*, Citation*, Generality* and Originality* equal the values of Patent Count, Patent Entities, Citation, Generality and Originality respectively before the log transformation, i.e., before adding one and taking the natural log. Furthermore, we also create country-team versions of the patent-based measures of innovation, in addition to the industry-country versions discussed above. For example, *Patent Count* ^{c} equals the natural logarithm of one plus the total number of eventually-granted patent applications filed in year t by applicants from country c. *Patent Entities* ^{c}, *Citation* ^{c}, *Generality* ^{c}, and *Originality* ^{c} are defined analogously.

Appendix Table A1 provides detailed variable definitions to the key variables used in our empirical analysis. Table 1 and Appendix Table A2 provide summary statistics of the five innovation measurements. In Table A2, the patent-based measures of innovation are averaged over the sample period. *Patent Count* ranges from an average of 0.05 patents per industry-year in Bangladesh to 468 per industry-year in Japan. The average number of truncation-adjusted citations for patents in an industry-year ranges from 0.06 in Swaziland to 9,620 in Japan. Table 1 further emphasizes the large dispersion in innovation across countries by pooling overall industry-country-years. On average, a country-industry have 36 eventually-granted patents filed with patent offices in 34 OECD countries and/or EPO in a particular year while the standard deviation is as high as 204. *Citation** is also highly dispersed. In an

[8] *Generality* and *Originality* are based on Hall et al. (2001), but we use the eight IPC sections, while they self-design six technological categories based on the US Patent Classification System. Thus, we use the IPC section to calculate the Herfindahl indexes of the generality and originality values of each patent. We then sum these values for patents within each IPC subclass. There are about 600 subclasses within the PATSTAT, which correspond closely in terms of granularity to the 400 categories (i.e., the three-digit classification) under the U.S. patent classification system.

average industry-country-year, the average value of *Citation** is 442 with a standard deviation of 3,526.

3. Empirical strategies

This section describes two strategies for identifying the impact of the enforcement of insider trading laws on the patent-based proxies of innovation and then presents evidence regarding the validity of these approaches. The first strategy is a simple difference-in-differences regression that assesses whether the proxies of innovation rise after a country first enforces its insider trading laws. The second strategy differentiates among industries within the same country and assesses whether the cross-industry patterns of changes in the innovation proxies after a country first enforces its insider trading laws is consistent with some theories and not with others. The second strategy, therefore, is essentially a triple difference regression.

3.1 Baseline strategy

We begin with the following simple difference-in-differences specification:

$$Innovation_{i,c,t} = \alpha_0 + \alpha_1 Enforce_{c,t} + \gamma X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}. \tag{1}$$

$Innovation_{i,c,t}$ is one of the five patent-based measures of innovation in industry *i*, of country *c*, in year *t*: *Patent Count*, *Patent Entities*, *Citation*, *Generality*, and *Originality*. The regressor of interest is $Enforce_{c,t}$, which equals one in the years after a country first enforces its insider trading laws, and zero otherwise. The regression includes country (δ_c), industry (δ_j), and time (δ_t) fixed effects to control for unobservable time-invariant country and industry characteristics, as well as all contemporaneous correlations across observations in the same year.

Besides the country, industry, and year fixed effects, the regression also includes time-varying country and industry characteristics (*X*). We include the natural logarithm of

Gross Domestic Product (*GDP*) and the natural logarithm of GDP per capita (*GDP per capita*) because richer countries may be more innovative and more active in filing patents with patent offices in more developed OECD countries, such as USPTO (Acharya and Subramanian 2009), than less well developed economies. We also control for stock market capitalization (*Stock/GDP*) and domestic credit provided by the financial sector (*Credit/GDP*) because Hsu et al. (2014) shows that financial market development influences innovation. These country level control variables are obtained from the World Development Indicators (WDI) database and the Financial Development and Structure (FDS) database (Beck et al. 2009) via the World Bank. At the industry-country-time level, we control for the ratio of each industry's exports to the U.S. over its country's total exports to the U.S. in each year (*Export to US*). We control for *Export to US* because the propensity to export to developed countries (e.g., U.S.) is positively associated with the industry's tendency to file patents in those countries (Bravo-Biosca 2007). The sample varies across specifications due to the availability of these control variables.

The coefficient, α_1, on *Enforce* provides an estimate of what happens to the patent-based measures of innovation after the country first enforces its insider trading laws, conditioning on the various fixed effects and other control variables specified in equation (1). Throughout the analyses, we use two-way clustering of the errors, at both the country and year level.

There are several challenges and limitations, however, associated with using the coefficient estimate, α_1, to assess different views about the impact of insider trading laws on innovation. First, reverse causality might hinder the ability to draw sharp inferences from α_1. The rate of innovation, or changes in the rate of innovation, might influence when countries enact and enforce their insider trading laws. Thus, we provide information below on the degree to which patent-based measures of innovation predict the timing of the enforcement of insider trading laws. We find no evidence that such patent-based measures forecast when countries start enforcing their insider trading laws.

Second, omitted variables might bias the results. Factors omitted from equation (1) might change at the same time as the country starts enforcing insider trading and it might be these omitted factors that shape subsequent innovation, not the enforcement of insider trading laws. Without controlling for such factors, we cannot confidently infer the impact of the enforcement of insider trading laws on innovation from α_1.

Third, as described in the Introduction and discussed in greater detail below, different theories offer different views about the mechanisms through which the enforcement of insider trading laws influences technological innovation. These views provide different predictions about which industries will be most affected by the enforcement of insider trading laws. Since equation (1) does not distinguish among industries, we cannot use it to differentiate among such views.

3.2. Industry-based empirical strategy

The industry-based empirical strategy addresses challenges and limitations associated with the baseline specification by assessing whether the enforcement of insider trading laws differentially affects innovation across industries in a manner that is consistent with particular theories. The industry-based regression specification augments the baseline model with an interaction term between *Enforce* and theoretically-motivated industry traits, *Industry*, and with more granular fixed effects:

$$Innovation_{i,c,t} = \beta_0 + \beta_1 Enforce_{c,t} \times Industry_i + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}. \quad (2)$$

$Industry_i$ measures industry traits, which we define below, that are the same across all countries and years. With the industry-based empirical strategy, equation (2) now controls for country-time and industry-time fixed effects. The country-time effect controls for all time-varying and time invariant country characteristics, while the industry-year effect absorbs all time-varying and time invariant industry traits. We do not include *Enforce*, *Industry*, and all of the control variables included in equation (1), except *Export to US*, separately in equation

(2) because they are subsumed in the fixed effects. The coefficient on the interaction term (β_1) provides an estimate of the differential change in innovation across industries after a country first enforces its insider trading laws.

Before discussing the particular industry traits, $Industry_i$, that we use in estimating equation (2), we describe in broad terms how moving to the industry-based strategy addresses the three analytical and interpretational weaknesses with the baseline specification discussed above. First, by distinguishing among industries, we assess different theoretical predictions about which industries will be most affected by the enforcement of insider trading laws. Second, differentiating among industries reduces concerns about omitted variable bias by focusing on how the enforcement of insider trading laws differentially affects innovation across industries in the same country. Formally, we control for country-time and industry-time fixed effects and thereby condition out all time-varying country factors that might be changing at the same time as the country starts enforcing insider trading laws as well as all time-varying industry-level changes. Finally, this strategy reduces concerns about reverse causality biasing the coefficient estimates. When employing this industry-based strategy, the results cannot be driven by a country's aggregate rate of innovation shaping the timing of when the country's authorities choose to enforce insider trading laws because we control for country-time fixed effects and conduct the analyses at the industry level.

Given this overview, we now describe the theoretically-motivated industry traits that we use when estimating equation (2). These categories primarily distinguish the view that the enforcement of insider trading promotes innovation by enhancing the incentives of investors to research firms, which lowers informational asymmetries and facilitates the valuation of innovative projects, from other views, including the hypothesis that enforcement affects innovation by increasing stock market liquidity.

The first category of industry traits measures the "natural rate" of innovation in each industry. More specifically, if the enforcement of insider trading laws promotes innovation by removing an impediment to the market accurately evaluating innovations, then enforcement should have a particularly pronounced effect on innovation in those industries that had been most severely hampered by the impediment: "naturally innovative" industries. To measure which industries are naturally innovative, i.e., industries that innovate more rapidly than other industries when national authorities enforce insider trading laws, we follow Rajan and Zingales (1998) and use the U.S. as the benchmark country for defining the natural rate of innovation in each industry and construct and use three specific variables based on the U.S. data.

The first measure of the natural rate of innovation is *High Tech*, which is a dummy variable that designates whether an industry is technology intensive or not. Based on the work of Hsu et al. (2014), we first calculate high-tech intensiveness as the annual percentage growth rate in R&D expenses for each publicly listed U.S. firm in each year. We then use the cross-firm average within each two-digit SIC industry as the measurement of high-tech intensiveness in a particular industry-year. We next take the time-series average over our sample period (1976-2006) to obtain a high-tech intensiveness measure for each industry. Finally, *High Tech* is assigned the value of one if the corresponding industry measurement is above the sample median and zero otherwise. Throughout the analyses, we use similar zero-one industry categorizations for values below or above the sample median. However, all of the results reported below hold when using continuous measures of the industry traits instead of these zero-one measures.

The second measure of whether an industry is naturally innovative is *Innovation Propensity.* To construct this variable, we follow Acharya and Subramanian (2009) and focus on (eventually-granted) patents that are filed with the USPTO during our sample period. First, for each U.S. firm in each year, we determine the number of patents that it applies for in each U.S. technological class defined in the Current U.S. Class (CCL) system. Second, for each U.S. technological class in each year, we compute the average number of patents filed by a U.S. firm. Third, we take the time-series average over the sample period within each technological class. Fourth, we map this to SIC industries using the mapping table compiled by Hsu *et al.* (2014) and obtain each industry's U.S. innovation propensity at the two-digit

SIC level. The indicator variable *Innovation Propensity* is set to one if the industry measure is above the sample median and zero otherwise.

The third measure of whether an industry is naturally innovative is its growth potential. Although not a direct measure of innovation, industries with naturally greater growth potential might be impeded more by insider trading than industries with weaker growth prospects, so that the enforcement of insider trading laws will unleash a bigger jump in innovation in those industries with naturally high growth potential. To measure an industry's natural growth potential—what its growth would be in the absence of many growth impediments, including those created by insider trading—we use the average market-to-book equity ratio of publicly listed U.S. firms in each industry. Though subject to potential limitations, higher market-to-book values are frequently used to gauge investment opportunities with larger values signaling greater growth potential. Thus, as an indicator of an industry's natural growth potential, we construct and use the variable *MTB*—which equals one if the market-to-book value of an industry in the U.S. is greater than the sample median and zero otherwise.

The second category of industry traits measures the natural opacity of each industry, i.e., the difficulty of the market formulating an accurate valuation of firms in the industry. If the enforcement of insider trading laws boosts innovation by encouraging markets to overcome informational asymmetries, then we should observe a larger increase in innovation in those industries that had been most hampered by informational asymmetries. To measure which industries are naturally opaque, we again use the United States as the benchmark country in constructing measures of opacity.

The first measure of whether an industry is naturally opaque is *Intangibility*, which measures the degree to which the industry has a comparatively large proportion of intangible assets. We use this measure under the assumption that intangible assets are more difficult for outsider investors to value than tangible assets, which is consistent with the empirical findings in Chan et al. (2001). To calculate *Intangibility*, we start with the accounting value of the ratio of Property, Plant and Equipment (PPE) to total assets for each firm in each year, where PPE is a common measure of asset tangibility (e.g., Baker and Wurgler 2002; Molina 2005). We then calculate the average of the PPE to total assets ratio across firms in the same industry-year and take the average over the sample period (1976-2006) for each industry. We next compute one minus the PPE-to-total-assets ratio for each industry. Throughout the construction, we use U.S. firms to form this industry benchmark. Finally, we set *Intangibility* equal to one for industries in which one minus the PPE-to-total assets ratio is greater than the median across industries and zero otherwise.

As a second measure of the degree to which an industry is naturally opaque, we use the standardized dispersion of the market-to-book value of firms in U.S. industries, where the standardization is done relative to the average market-to-book equity ratio of publicly listed U.S. firms in each industry. Intuitively, wider dispersion of the market-to-book values indicates a greater degree of heterogeneity in how the market values firms in the same industry. This greater heterogeneity, in turn, can signal more firm opaqueness as the other firms in the same industry do not serve as good benchmarks. Following Harford (2005), we calculate the within-industry standard deviation of the market-to-book ratio across all U.S. publicly listed firms in each industry-year and take the average over time to measure market-to-book dispersion in each U.S. industry. We then standardize the market-to-book dispersion by dividing it by the average market-to-book value of each industry. Accordingly, *STD of MTB* equals one for observations above the cross-industry median and zero otherwise.

The third category of industry traits that we use to assess the predictions that different theories make about the impact of the enforcement of insider trading laws on cross-industry changes in innovation is liquidity. In particular, one set of theories predicts that the enforcement of insider trading laws will boost stock market liquidity and this increase in stock market liquidity can affect innovation. If this liquidity mechanism is an important channel linking the enforcement of insider trading to innovation, then the effects of enforcement should be especially pronounced in industries that are naturally liquid, i.e., in industries that would have high levels of liquidity if the authorities enforced their insider trading laws. We again use the U.S. financial market as a benchmark, under the assumptions that (a) U.S. markets provide a valuable signal of the comparative liquidity of stocks in different industries in a comparatively efficient market and (b) enforcing insider trading laws will increase the efficiency of markets.

To construct a measure of the natural illiquidity of each industry, we start with the average daily Amihud illiquidity measure (AIM) (Amihud 2002) of publicly-traded U.S. firms. The daily AIM gauges the degree to which a stock's price responds to trading and is defined as the price impact of a one million dollar trading volume, i.e., [1,000,000 x abs(return)]/[trading volume]. Greater values indicate less liquidity. Then, we compute the average AIM for each firm-year, where the averaging is done across the firm's daily AIM. Next, we compute the average AIM for each industry-year by taking the average across all firms within each industry in each year. Then, we average across all industry-years within the sample period for each industry. We set *Illiquidity* equal to one if a U.S. industry has AIM above the sample median and zero otherwise.

There might be concerns that the first category of industry traits that focuses on naturally innovative industries is empirically and conceptually related to the second category that focuses on naturally opaque industries because there tend to be comparatively high costs to valuing innovative endeavors. However, in only 23% of industries are *High Tech* and *Intangibility* both equal to one.[9] They are also conceptually distinct. For example, two industries might be equally opaque, but one might be more naturally innovative. In this case, the enforcement of insider trading laws would enhance the valuation of both industries but it would spur a larger jump in innovation in the more naturally innovative industry. Similarly, two industries might have equal degrees of natural innovativeness, but one might be more opaque. In this case, the enforcement of insider trading laws would have a bigger impact on valuations in the more opaque industry and therefore have a bigger impact innovation in the naturally more opaque industry. Thus, we examine both categories of industry traits, while recognizing that there is overlap.

[9] Only 35% of the industries that are categorized as *either* innovative or opaque, are labeled as both innovative and opaque.

3.3 Preliminary evidence regarding the validity of these strategies

In this subsection, we present three types of analyses that advertise the validity and value of our empirical strategy. To assess the assumption that the initial enforcement of insider trading laws is not driven by pre-existing innovative activities, we start by plotting the year that a country first enforces its insider trading against (1) the patent-based measures of innovation in the years before a country first enforced its insider trading laws and (2) the rate of change of these patent-based measures of innovation before enforcement. Thus, *Figure 1* provides two plots for each of the patent-based measures of innovation. We exclude countries in which authorities started enforcing their insider trading laws before the start of the sample period. As portrayed in *Figure 1*, neither the levels nor the rates of change in the innovation proxies predict the timing of the initial enforcement of insider trading laws. While by no means definitive, this mitigates some concerns about reverse causality.

Second, we employ a hazard model to study the factors shaping when countries first enforce their insider trading laws. In particular, we test whether patent-based measures of innovation predict when a country first brings a prosecution against insider trading in a given year conditional on the fact that no such prosecution had ever been initiated. We assume the hazard rate follows a Weibull distribution and use the natural log of survival time (i.e., expected time to the initial enforcement) as the dependent variable, where longer time indicates lower likelihood of being enforced. As the key explanatory variables, we use country-year measures of innovation. Specifically, *Patent Count*^{c} is the natural logarithm of one plus the total number of eventually-granted patent applications filed in year t by applicants from country c. *Patent Entities*^{c} is the natural logarithm of one plus the total number of distinct entities in country c that apply for patents in year t. *Citation*^{c}, *Generality*^{c}, and *Originality*^{c} are defined similarly.

As reported in *Table 2*, pre-existing patent-based measures of innovation do not predict the timing of the first enforcement action. The Wald test of their joint significance is provided at the bottom of the table. Furthermore, the absence of predictive power holds when controlling for economic and financial development (*GDP*, *GDP per capita*, *Stock/GDP*, and *Credit/GDP*), as shown in column (2), or when also controlling for the legal origin of the country in column (3). We control for legal origin, i.e., whether the country has common law, French civil law, German civil law, or Scandinavian civil law heritage, because La Porta et al. (1998) and the subsequent literature emphasize how legal heritage can influence an assortment of laws concerning financial contracting.[10] Thus, there is no evidence that a country's rate of innovation predicts when it will start enforcing its insider trading laws.

Third, we examine the dynamic relationship between innovation and the first time that a country enforces its insider trading laws. Following Beck et al. (2010), we augment the baseline regression in equation (1) with a series of time dummies relative to the year of initial enforcement of the laws (*t=0*) and use the following:

$$\mathrm{Innovation}_{\mathrm{c,t}} = \alpha_0 + \alpha_{1,\tau} \sum_{\tau=t-10}^{\tau=t+15} \mathrm{Enforce}_{c,\tau} + \lambda X'_{c,t} + \delta_c + \delta_t + \varepsilon_{c,t}, \text{ where } \tau \neq 0. \qquad (3)$$

Innovation$_{c,t}$ is one of the five patent-based measures of innovation and is calculated at the country-year level, so that *Patent Count*^{c} equals the natural logarithm of one plus the total number of eventually-granted patent applications filed in year *t* by applicants from country *c*, and *Patent Entities*^{c}, *Citation*^{c}, *Generality*^{c}, and *Originality*^{c} are defined similarly. $\mathrm{Enforce}_{c,\tau}$ is a dummy variable that equals one if the observation at time *t* is τ years away from the year of initial law enforcement. If τ is greater than zero, then the dummy identifies the τ^{th} year after the initial enforcement of the insider trading laws; if τ is smaller than zero, it represents the τ^{th} year before the initial enforcement. We include a total of 25 dummies to trace out the year-by-year effect on innovation from at most 10 years before the event to at most 15 years afterwards. At the end points, all the years over 10 years before the initial enforcement are captured by the dummy $\mathrm{Enforce}_{c,-10}$ while all the years beyond 15 years after the initial enforcement captured by the dummy $Enforce_{c,+15}$. The year of initial

[10] We extended these analyses. Instead of using the country-year measures of innovation that are based on all industries in each country, we use values based only on *High Tech* industries, i.e., industries as defined by high R&D expenditures in the U.S. We confirm the results in *Table 2*.

enforcement serves as the benchmark, hence it is dropped from the regression. We center the coefficients of the series of time dummies on the year of initial enforcement ($t=0$) and plot them against the years with respect to the enforcement year, together with the 95% confidence interval adjusted for country level clustering. In terms of control variables, $X_{c,t}$ includes *GDP*, *GDP per capita*, *Stock/GDP* and *Credit/GDP* and the regressions also include country and year fixed effects.

Figure 2 illustrates two crucial findings. First, there is a significant increase in the patent-based measures of innovation after a country starts enforcing its insider trading laws. Consistent with the view that enforcing insider trading laws encourages innovative activities, *Figure 2* depicts a 27% increase in *Patent Counts*^{c} after five years (from the centered value on the first enforcement date) and an even bigger increase in Citation^c over the same period. The second key finding confirms the results from the hazard model: There is not a strong trend in the patent-based measures of innovation prior to the year in which a country first enforces its insider trading laws. The overall pattern suggests that enforcing insider trading has an enduring simulative effect on the quantity and quality of patenting.

4. Empirical Results

In this section, we present results on the relationship between technological innovation and the enforcement of insider trading laws. We first use the simple baseline strategy to evaluate what happens to patent-based proxies of innovation after a country first enforces its insider trading laws. We then present the results from the industry-level strategy.

4.1 Baseline Specification

Table 3 presents the regression results from the simple baseline regression specification defined in Section 3. The table consists of five columns, one for each patent-based proxy, and two panels, where Panel A presents results in which the regressors besides *Enforce* are the country, industry, and year fixed effects and where, in Panel B, the regressions also include the time-varying country and industry characteristics defined above. Thus, *Table 3* presents the results from ten model specifications. In all of the regressions reported throughout the remainder of the paper, the standard errors are two-way clustered at both the country and year level, allowing for statistical inferences that are robust to correlations among error terms within both country and year clusters.

The results indicate that all of the patent-based measures increase materially after the average country first enforces its insider trading laws. *Enforce* enters with a positive and statistically significant coefficient in all ten regressions. The coefficient estimates also indicate that there is an economically large increase in the innovation measures after countries start enforcing their insider trading laws. For example, consider Panel B, which includes the broadest set of control variables. The results indicate that the initial enforcement of insider trading laws is associated with a 26% increase in *Patent Counts* (i.e., patenting intensity), a 21% increase in the number of *Patenting Entities* (i.e., scope of patenting activity), a 37% increase in *Citations* (i.e., impact), a 16% in *Generality* (i.e., breadth of impact on other technologies), and an 18% increase in *Originality* (i.e., breadth of other technologies cited).

Although the analyses in *Table 3* are fully consistent with the view that the enforcement of insider trading laws fosters innovation, these baseline regressions face the interpretational limitations discussed above. In particular, omitted variables that change at the same time that the country enforces its insider trading laws might affect subsequent innovation in the country and therefore lead to a biased estimate of the impact of enforcing insider trading laws on innovation. Furthermore, theory provides predictions about which industries will be most affected by the enforcement of insider trading laws, but the baseline regressions reported in *Table 3* do not evaluate these predictions. Thus, we now turn to the industry-based empirical strategy.

4.2 Differential Industry Responses Motivated by the Valuation View

In this subsection, we assess the valuation view's predictions about the cross-industry impact of the enforcement of insider trading laws on innovation. The valuation view holds that the enforcement of insider trading laws removes an impediment to the market fully and accurately valuing innovative projects of firms and encourages more investment in innovative activities that have positive net present values (NPV) when valued in a setting with no informational asymmetries between corporate insiders and outsiders. According to the valuation view, when a country starts enforcing its insider trading laws, this should have a particularly positive impact on innovation in those industries that had been most constrained by the absence of enforcement, such as (1) naturally innovative industries that would have had much faster rates of innovation except for the informational impediments created by the lack of effective limits on insider trading and (2) naturally opaque industries that the market would have more precisely valued if there had been effective restrictions on insider trading.

4.2.1 Differentiating by the natural innovativeness of industries

Table 4 presents our assessment of whether naturally high-tech industries (*High Tech*) experience larger increases in patent-based measures of innovation after a country starts enforcing its insider trading laws than other industries. There are five regressions, where the dependent variable is one of the five patent-based measures of innovation. The explanatory variable of interest is the interaction term, *High Tech*Enforce*, and the regressions also control for country-year and industry-year fixed effects, as well as each country-industry's exports to the U.S. in each year.

As shown, the patent-based measures of innovation rise much more in high-tech industries after a country first enforces its insider trading laws. For example, *Patent Counts* increase by 43% more in high-tech industries than in other industries, where a high-tech industry is one in which the average annual growth rate of R&D expenses over the sample period is greater than the median (using the U.S. to make these calculations for all industries). The large wedge between high-tech and other industries holds for the other patent-based measures of innovation. After a country first enforces its insider trading laws, high-tech industries experience larger increases in *Patenting Entities*, *Citations*, *Generality*, and *Originality* than other industries. By controlling for country-year effects, these results cannot be attributed to other changes that occur in the country at the same time as the first enforcement of insider trading unless those other changes also differentially affect industries in precisely this manner. Similarly, by controlling for industry-year effects, these results are not due to international increases in the rates of innovation in high-tech industries.

Table 5 presents similarly strong the results when differentiating industries by another proxy for the degree to which an industry is naturally innovative—*Innovation Propensity*, which equals one when the average number of patents per firm in the U.S. industry is greater than the median. The interaction term, *Innovation Propensity*Enforce* enter each of the regressions positively and significantly at the one percent level. The estimated effects are large. For example, in an average industry in the subset of industries with *Innovation Propensity* equal to one, *Patent Count* rises by 50% more than an average industry in the subset of industries with *Innovation Propensity* equal to zero after a country starts enforcing insider trading laws. These findings are also consistent with the valuation view of how the enforcement of insider trading laws shapes innovation.

Consistent with these results, *Table 6* indicates that industries with greater growth potential experience a much larger increase in the patent-based measures of innovation after a country first enforces its insider trading laws than industries with weaker growth prospects. In particular, we differentiate industries by growth potential under the assumption that growth potential provides additional information on the degree to which an industry is naturally innovative. We designate an industry as having high growth potential if the U.S. industry has higher than the median market-to-book value (*MTB*). We then regress each of the five patent-based measures of innovation on the interaction term between *MTB* and *Enforce*, along with the standard control variables used in these industry-based regressions. As shown in *Table 6*, the estimated coefficient on *MTB*Enforce* is positive and significant at the one percent level in each regression. Industries with comparatively high market-to-book ratios experience a 12% to 20% greater increase in the innovation measures after a country starts enforcing insider trading laws.

4.2.2 Differentiating by the natural opacity of industries

We next assess whether industries that are naturally opaque experience a bigger increase in innovative activity after a country first enforces its insider trading laws. As explained above, the valuation view argues that enforcing insider trading laws encourages potential investors to expend more resources valuing firms, so that enforcement will have a particularly positive impact on valuations—and hence innovation—in those industries in which informational asymmetries had most severely impeded the full valuation of positive NPV projects. As noted above, proxies for natural opacity might be correlated with the degree to which an industry is naturally innovative. Thus, we do not claim to identify independently the naturally innovative and opacity channels. Rather, we emphasize that the valuation view predicts that the enforcement of insider trading laws will have a particularly more pronounced and positive impact on innovation in both naturally innovative and opaque industries. We use an assortment of industry traits to assess this prediction.

Consistent with valuation view, the results reported in *Table 7* suggest that more opaque industries—as proxied by *Intangibility* = 1—experience a much larger increase in innovation after the enforcement of insider trading laws than other industries. Recall that *Intangibility* equals one if the proportion of intangible to total assets among firms in an industry is greater than the median industry (using U.S. data to categorize industries). The interaction term, *Intangibility*Enforce* enters positively and significantly at the one percent level in the *Patent Count*, *Patent Entities*, *Citation*, *Generality*, and *Originality* regressions. Furthermore, the effect is large. Across the different patent-based measures of innovation, innovation increases by 25% to 30% more in opaque industries than in other industries after a country starts enforcing its insider trading laws.

Using the standard deviation of the market-to-book ratio, *STD of MTB*, as an alternative proxy for informational opacity in *Table 8*, the results support the valuation view. As defined above, *STD of MTB* equals one for industries in which the within-industry standard deviation of the market-to-book ratio is above the median and zero otherwise. The results indicate that industries in which *STD of MTB* equals one enjoy a bigger increase in innovative activity after a country first enforces its insider trading laws than other industries. In particular, *STD of MTB*Enforce* enters positively and significantly in the *Patent Count*, *Patent Entities*, *Citation*, *Generality*, and *Originality* regressions, where the regressions continue to control for country-year effects, industry-year effects, and *Export to US*.

4.3 Differential Industry Responses: Liquidity

The results reported thus far are inconsistent with the view that enforcing insider trading laws reduces innovation, either by increasing liquidity or through some other mechanism. Rather, the results indicate the enforcement of insider trading laws spurs patenting activity in a cross-industry manner that is consistent with the valuation view.

We now provide a more direct assessment of the liquidity view. We assess whether enforcing insider trading laws affects patenting activity differently in naturally liquid industries. This would occur if enforcement disproportionately increases the liquidity of the shares of firms in naturally liquid industries and the increase in liquidity affects innovation through the mechanisms discussed above. We measure the natural illiquidity of an industry's shares, *Illiquidity*, using the Amihud illiquid measure. In particular, *Illiquidity* equals one if the average value of the Amihud illiquidity of U.S. firms in an industry is greater than the sample median.

Table 9 provides no support for the liquidity view. There is not a statistically significant difference in the change in the patent-based measures of innovation between naturally illiquid or liquid industries after a country starts enforcing insider trading laws. That is, the interaction term, *Illiquidity*Enforce*, does not enter significantly in the *Patent Count*, *Patent Entities*, *Citation*, *Generality*, or *Originality* regressions. The positive association between innovation and the enforcement of insider trading laws is neither larger nor smaller in industries with naturally illiquid shares.

5. Equity Issuances

One channel through which the enforcement of insider trading laws may affect innovation is by facilitating the issuance of equity. In particular, the valuation view holds that effective constraints on insider trading will enhance the valuation of innovative activities and thereby encourage equity issuances by such firms. This can occur in several ways.

If innovators and investors can eventually capitalize on successful innovations by issuing equity at prices that more fully value the innovation, this will foster investment in the costly and risky process of creating those innovations. According to Aggarwal and Hsu (2014), initial public offerings (IPOs) and acquisition by another entity are two major exit routes that provide financial returns to entrepreneurs and investors. For start-ups, enforcing insider trading laws can incentivize innovative endeavors *ex ante* by improving the expected valuation during future IPOs. Similarly, for entrepreneurs that exit via acquisitions, particularly in the form of stock swaps, enforcing insider trading laws can also encourage innovative endeavors *ex ante* by increasing the expected prices of such acquisitions, as reflected, for example, in the terms of future stock swaps. More generally, to the extent that public acquirers can issue new shares that correctly price the innovations owned by target companies, this increases the expect returns to potential targets from investing in innovation in the first place.

Furthermore, the enforcement of insider trading laws can stimulate innovation by facilitating seasoned equity offerings (SEOs). For publicly listed firms, effective insider trading laws can increase the accuracy with which markets value innovative activities and thereby facilitate SEOs. Having shown above that the enforcement of insider trading laws is associated with a sharp increase in patenting activity in naturally innovative industries, we now assess whether this is associated with a surge in equity issuances as well.

Motivated by these predictions, we test whether firms in naturally innovative industries issue more equity than those in other industries after a country's authorities start enforcing insider trading laws. To distinguish naturally innovative industries from other industries, we again use *High Tech* and *Innovation Propensity*. We use nine measures of equity issuances. For each industry-country-year, we calculate the natural logarithm of one plus the number of IPOs (*IPO Number*), the natural logarithm of one plus the proceeds of those IPOs in U.S. dollars (*IPO Proceeds*), and the natural logarithm of one plus the average amount raised (in U.S. dollars) per IPO (*Proceeds per IPO*). We calculate similar measures for SEOs (*SEO Number*, *SEO Proceeds*, and *Proceeds per SEO*) and for total of IPOs and SEOs in each industry-country-year (*Total Issue Number*, *Total Proceeds*, and *Proceeds per Issue*).

Specifically, we estimate the following equation:

$$Equity\ Issuance_{i,c,t} = \beta_0 + \beta_1 Enforce_{c,t} \times Industry_i + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}, \quad (4)$$

where $Equity\ Issuance_{i,c,t}$ is one of the nine measures of equity issuances and $Industry_i$ is either *High Tech* or *Innovation Propensity*. We continue to include country-year and industry-year fixed effects and to control for the ratio of country-industry-year exports to the U.S. as a share of the country's total exports to the U.S. in that year (*Export to US*). *Table 10* provides the regression results. Panel A provides the results from nine regressions in which the interaction term is *Enforce*High Tech*, while Panel B provides the results in which the interaction term is *Enforce*Innovation Propensity*.

As shown in *Table 10*, equity issuances increase substantially more in naturally innovative industries than in other industries after a country first enforces its insider trading laws. Across the nine regressions in Panel A, the estimated coefficient on *Enforce*High Tech* enters positively and significantly at the one percent level. The results are equally strong when examining the interaction term of *Enforce*Innovation Propensity* in Panel B. In all cases, the number of equity issuances, the amount raised through those issuances, and the average size of the issuances all increase more in naturally innovative industries after insider trading laws are first enforced. These results hold when considering IPOs, SEOs, or the total number and value issuances.

The estimated magnitudes are large. For example, the *Table 10* estimates indicate that enforcing insider trading laws is associated with 38% larger increase in *IPO Proceeds* in industries in which *Innovation Propensity* equals one than in industries in which *Innovation Propensity* equals zero. As another example, the reported estimates in *Table 10* suggest that when a country starts enforcing insider trading laws, this is associated with a 32% larger boost in *SEO Proceeds* in industries with a naturally fast growth rate of R&D expenditures (i.e., *High Tech* =1) as compared with other industries. The results are consistent with the view that the enforcement of insider trading laws facilitates equity issuances by naturally innovative industries.

6. Conclusion

In this paper, we discover that the enforcement of insider trading laws is associated with a sharp increase in patent-based measures of innovation. Based on about 75,000 industry-country-year observations across 94 economies from 1976 to 2006, we find that intensity, scope, impact, generality, and originally of patenting activity all rise markedly after a country first starts enforcing its insider trading laws. The evidence is consistent with theories predicting that the protection of outside investors from insider trading fosters technological innovation.

We also examine whether changes in the cross-industry pattern of the patent-based measures of innovation following the enforcement of insider trading lows are consistent with some theories of how insider trading shapes innovation and inconsistent with others. In these analyses, we control for country-year and industry-year fixed effects to better isolate the relationship between innovation and restrictions on insider trading.

The cross-industry results further emphasize the positive link between restrictions on insider trading and innovation. In particular, the valuation hypothesis holds that if insiders can trade on non-public information, this will dissuade other investors from expending the resources necessary for accurately valuing innovative activities and this will impede the efficient allocation of capital to innovative endeavors. This has testable implications: The enforcement of insider trading laws should have a particularly pronounced effect on (1) naturally innovative industries— industries that would have experienced rapid innovation if insider trading had not impeded accurate valuations—and (2) naturally opaque industries—industries that would experience more investment if insider trading has not impeded accurate valuations. This is what we find. The relationship between enforcing insider trading laws and innovation is much larger in industries that are naturally innovative and opaque, where we use U.S. industries to categorize industries by innovativeness and opacity.

The results from our examination of equity issuances are also consistent with the predictions of the valuation view. The valuation view implies that since insider trading impedes the ability of markets to accurately value innovative activities and this reduces equity issuances by such firms. Our evidence confirms this prediction. We discover that industries that are naturally more innovative experience a much bigger increase in equity issuances after a country starts enforcing its insider trading laws than other types of industries.

Taken together, our findings suggest that laws, regulations, and enforcement mechanisms that foster that ability of markets to value firms accurately exert a material impact on innovation and hence living standards. The evidence suggests that the ability of firms to capitalize on successful innovation *ex post* can enhance incentives for investment in innovative endeavors *ex ante*. Since innovation is vital for sustaining improvements in living standards, these results highlight the centrality of financial market policies.

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Appendix

Table A1. Variable Definitions

This table provides definition and data sources of all the variables used in the analysis. They are grouped into five categories related to insider trading laws, patent-based measures of innovation, the economic and legal development of each country, industry characteristics, and equity issuance activities.

Variable	Definition	Source
	Insider Trading Law (IT Law)	
Enforce	An indicator variable equal to one in the years after a country first enforces its insider trading laws, and equals zero otherwise; it equals zero for those years in which a country does not have insider trading laws. The latest information is by the year of 2002.	Bhattacharya and Daouk (2002)
	Patent-Based Innovation Measures	
Citation	The natural logarithm of one plus the total number of forward citations made to (eventually-granted) patents in industry *i* that are filed with patent offices in one of the member countries of the Organization for Economic Cooperation and Development (OECD) and/or European Patent Office (EPO) in year *t* by applicants in country *c*; if there are more than one patent for a particular invention (i.e. multiple patents being part of the same DOCDB patent family), either the citing invention or the cited one, we only count one citation regardless of the actual patent(s) citing or being cited between two patent families, and we use the bibliographic information of the first patent in a patent family to determine the year, the International Patent Classification (IPC) subclass and the country of the invention; since citations beyond the coverage of PATSTAT (i.e., the full years after 2014) are not observed, we adjust for the actually-observed citation count of a patent family granted after 1985 by dividing it by the weighting factor corresponding to its IPC section (*K*) and the lag between its year of grant and 2014 (*L*): $W_L^K, L = 0, \ldots, 28$; $W_L^K = 1/\bar{S}_L^K$, where $\bar{S}_L^K$ is the estimated cumulative share of citations having been received since the grant of the patent in IPC section *K* for *L* years over a 30-year lifetime; we calculate S_L^K based on the patents granted in each of the ten years between 1976-1985 respectively (1985 is the last year with 30 years' observations) and define $\bar{S}_L^K$ as the average across the ten estimates for each *K* each *L*; citations to patent families granted on and before 1985 are not adjusted; then, the (adjusted) citation count is summed over all the patent families in a particular IPC subclass, converted to International Standard Industry Classification (ISIC) using the concordance provided by Lybbert and Zolas (2012), and further to the two-digit Standard Industry Classification (SIC) industry level using the concordance by the United Nations Statistical Division. Citation* is Citation before the log transformation. *Citation*^{c} is the natural logarithm of one plus the total number of citations to patent families that are filed in year *t*, in country *c*. The concordance in Lybbert and Zolas (2012) is available at http://www.wipo.int/econ_stat/en/economics/publications.html The concordance from ISIC to SIC is available at http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1	PATSTAT Database
Generality	The natural logarithm of one plus the sum of the generality score of all the (eventually-granted) patents in industry *i* that are filed with patent offices in one of the OECD countries and/or EPO in year *t* by applicants in country *c*; the generality score of each patent is defined as the one minus the Herfindahl Index of the IPC sections of patents citing it; the higher the generality score, the more generally applicable the patents is for other types of innovations; the score is	PATSTAT Database

	first aggregated at IPC level, then converted to ISIC using the concordance provided by Lybbert and Zolas (2012), and further to the two-digit SIC industry level using the concordance by the United Nations Statistical Division. Generality* is Generality before the log transformation. *Generality* ^{c} is the natural logarithm of one plus the sum of the generality score of all the patents that are filed in year *t* by applicants from country *c*.	
Originality	The natural logarithm of one plus the sum of the originality score of all the (eventually-granted) patents in industry *i* that are filed with OECD countries and/or European Patent Office (EPO) in year *t* by applicants in country *c*; the generality score of each patent is defined as the one minus the Herfindahl Index of the IPC sections of patents that it cites; the higher the originality score, the wider range of technologies it draws upon; the score is first aggregated at IPC subclass level, then converted to ISIC using the concordance provided by Lybbert and Zolas (2012), and further to the two-digit SIC industry level using the concordance by the United Nations Statistical Division. Originality* is Originality before the log transformation. *Originality* ^{c} is the natural logarithm of one plus the sum of the originality score of all the patents that are filed in year *t* by applicants from country *c*.	PATSTAT Database
Patent Count	The natural logarithm of one plus the total number of eventually-granted patent applications belonging to industry i that are filed with the patent offices in one of the 34 OECD countries and/or the EPO in year t by applicants from country c; if there are more than one patent for a particular invention (i.e. multiple patents being part of the same DOCDB patent family), we count the first patent and use its bibliographic information to determine the year, the IPC subclass and the country of the invention; the total number is first calculated at IPC subclass level, then converted to ISIC using the concordance provided by Lybbert and Zolas (2012), and further mapped to the two-digit SIC industry level using the concordance by the United Nations Statistical Division. Patent Count* is Patent Count before the log transformation. *Patent Count* ^{c} is the natural logarithm of one plus the total number of eventually-granted patent applications filed in year *t* by applicants from country *c*.	PATSTAT Database
Patent Entities	The natural logarithm of one plus the total number of distinct entities in country c, that apply for patents (eventually-granted) in industry i in year t with the patent offices in one of the 34 OECD countries and/or the EPO; the total number is first calculated at IPC subclass level, then converted to ISIC using the concordance provided by Lybbert and Zolas (2012), and further to the two-digit SIC industry level using the concordance by the United Nations Statistical Division. Patent Entities* is Patent Entities before the log transformation. *Patent Entities* ^{c} is the natural logarithm of one plus the total number of distinct entities in country *c* that apply for patents (eventually-granted) in year *t*.	PATSTAT Database
	Country Development	
Credit/GDP	Domestic credit provided by financial sector over GDP; the credit includes all credit to various sectors on a gross basis, with the exception of credit to the central government; the financial sector includes monetary authorities, deposit money banks, as well as other financial corporations such as finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange	World Bank-WDI

	companies.	
FRSP Origin	French or Spanish legal origin	LLSV (1998)
GDP	The natural logarithm of Gross Domestic Product (GDP) measured in current U.S. dollar	World Bank-WDI
GDP per capita	The natural logarithm of GDP per capita measured in current U.S. dollar	World Bank-WDI
GER Origin	German legal origin	LLSV (1998)
SCAN Origin	Scandinavia legal origin	LLSV (1998)
Stock/GDP	The value of listed shares to GDP	World Bank -FDS
UK Origin	UK legal origin	LLSV (1998)
	Industry Characteristics	
Export to US	The ratio of each industry's export to the U.S. over its country's total export to the U.S. in each year; the data is provided at the Standard International Trade Classification level (SITC Rev1) and we map it to the two-digit SIC level via Harmonized System (H0) using the concordance schemes provided by the World Bank http://wits.worldbank.org/product_concordance.html	UN Comtrade
High Tech	An indicator variable based on the high-tech intensiveness of each two-digit SIC industry; we first calculate the average annual percentage growth of R&D expenses (Compustat item *xrd*) over all the U.S. public firms in each industry-year; then we use the time-series average within each industry over the sample period (1976-2006) as the measurement of high-tech intensiveness at industry level; High Tech is set to 1 if it is above the sample median and 0 otherwise.	Compustat
Illiquidity	An indicator variable based on the Amihud illiquidity measurement (AIM) (Amihud 2002) of each two-digit SIC industry: we first calculate daily AIM for each U.S. public firm using this formula (CRSP item: Daily AIM = $1000000 \times \text{abs}(ret) / (price \times vol)$); we then take average across daily AIM for each firm-year; we next take average across the AIM of all firms in each industry-year and use the time-series average within each industry over the sample period (1976-2006) as the industry-level measurement; Illiquidity is set to 1 if it is above the sample median and 0 otherwise.	CRSP
Innovation Propensity	An indicator variable based on the innovation propensity measure for each two-digit SIC industry; we first calculate the average number of patents filed by a U.S. firm in each three-digit U.S. technological class in each year; we then calculate the time-series average within each technological class over the sample period (1976-2006); after obtaining the measurement at the three-digit technological class, we convert it to the two-digit SIC level using the mapping scheme provided by Hsu et al. (2014); Innovation Propensity is set to 1 if it is above the sample median and 0 otherwise.	NBER Patent Database
Intangibility	An indicator variable based on the intangibility of each two-digit SIC industry: we first calculate the average ratio of Plant, Property and Equipment (PPE) (Compustat item *ppent*) over total assets (Compustat item *at*) across all the U.S. public firms in an industry-year; we then use the time-series average within each industry over the sample period (1976-2006); we next compute one minus the PPE/Asset ratio as the proxy for intangibility in each industry; Intangibility is set to 1 if it is above the sample median and 0 otherwise.	Compustat
MTB	An indicator variable based on the average market-to-book equity ratio of each two-digit SIC industry: we first calculate the average market-to-book ratio (Compustat item $(csho \times prcc)/ceq$) across all	Compustat

	the U.S. public firms in each industry-year; we then use the time-series average within each industry over the sample period (1976-2006) as the market-to-book ratio measurement at industry level; MTB is set to 1 if it is above the sample median and 0 otherwise.	
STD of MTB	An indicator variable based on the standard-deviation of market-to-book equity ratio in each two-digit SIC industry: we first calculate the standard deviation of market-to-book ratio (Compustat item (*csho*×*prcc*)/*ceq*) across all the U.S. public firms in each industry-year; we then compute the time-series average within each industry over the sample period (1976-2006); we next divide the dispersion of market-to-book ratio at industry-level by the average market-to-book ratio in the same industry, where the denominator is firm-level market-to-book ratio averaged within each industry-year and then across industry-years; MTB_STD is set to 1 if it is above the sample median and 0 otherwise.	Compustat
	Equity Issuance Activities	
IPO Number	The natural logarithm of one plus the total number of initial public offering (IPO) in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
IPO Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) raised via IPO in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
Proceeds per IPO	The natural logarithm of one plus the average amount of dollar proceeds per IPO (mil$) made in an industry- country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
Proceeds per Issue	The natural logarithm of one plus the average amount of dollar proceeds per equity issuance (mil$) made in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
Proceeds per SEO	The natural logarithm of one plus the average amount of dollar proceeds per SEO (mil$) made in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
SEO Number	The natural logarithm of one plus the total number of seasoned public offering (SEO) in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
SEO Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) raised via SEO in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
Total Issue Number	The natural logarithm of one plus the total number of equity issuance in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC
Total Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) raised from the equity market in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC

Table A2. Country-level Information of Insider Trading Laws and Innovation

This table presents basic information on the enactment year (*Exist Year*) and enforcement year (*Enforce Year*) of the insider trading laws, together with summary statistics of the patent-based measures of innovation by country. There are a total of 94 countries in the full sample between 1976 and 2006 (U.S. is included for illustration purpose). *Patent Count** is the total number of eventually-granted patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities** is the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation** is the total number of citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality** and *Originality** are the sum of the generality and originality scores, respectively of all the patents in industry *i* that are applied in year *t* by applicants from country *c*. We restrict to patents filed and granted by the patent offices in one of the 34 OECD countries and/or EPO and we work with patent families to define the patent-based measures of innovation. When reporting the summary statistics for each country of these patent-based measures of innovation, we take the unweighted average across industry-year observations within the sample period 1976-2006. Industry-country-year without patent information is not included in the sample. Industry is defined on two-digit SIC. Appendix Table A1 provides detailed definitions of the variables.

Country Particulars		Insider Trading Law		PATSTAT Patent Measurements				
Country Name	OECD Members	Exist Year	Enforce Year	Patent Count*	Patent Entities*	Citation*	Generality*	Originality*
Argentina		1991	1995	0.75	0.93	10.93	0.11	0.13
Armenia		1993	no	0.09	0.13	0.21	0.03	0.02
Australia	yes	1991	1996	10.27	12.98	234.46	2.09	2.20
Austria	yes	1993	no	25.86	26.56	140.24	2.18	3.32
Bahrain		1990	no	0.09	0.13	0.79	0.01	0.01
Bangladesh		1995	1998	0.05	0.11	0.40	0.01	0.02
Barbados		1987	no	1.22	0.83	50.87	0.22	0.20
Belgium	yes	1990	1994	10.55	10.58	150.06	1.81	2.18
Bermuda		no	no	0.94	0.72	30.29	0.19	0.23
Bolivia		no	no	0.11	0.15	1.29	0.02	0.01
Brazil		1976	1978	1.51	1.97	17.05	0.24	0.29
Bulgaria		no	no	0.68	0.80	16.24	0.07	0.08
Canada	yes	1966	1976	50.01	51.56	1212.21	10.95	10.68
Chile	yes	1981	1996	0.26	0.38	2.50	0.04	0.06
China		1993	no	5.87	6.04	151.17	1.07	1.47
Colombia		1990	no	0.19	0.24	2.56	0.03	0.04
Costa Rica		1990	no	0.16	0.16	2.07	0.02	0.03
Croatia		1995	no	0.40	0.48	4.24	0.05	0.08
Cyprus		1999	no	0.34	0.42	7.29	0.06	0.08
Czech Republic	yes	1992	1993	3.47	3.63	10.54	0.17	0.27
Denmark	yes	1991	1996	9.72	10.73	150.49	1.57	1.79
Ecuador		1993	no	0.10	0.18	1.48	0.02	0.03
Egypt		1992	no	0.12	0.17	2.33	0.01	0.01
El Salvador		no	no	0.13	0.17	0.45	0.02	0.01
Estonia	yes	1996	no	0.34	0.45	2.03	0.02	0.03
Finland	yes	1989	1993	23.60	21.01	396.62	3.20	3.63
France	yes	1967	1975	189.83	176.92	1373.03	21.44	30.38
Germany	yes	1994	1995	338.86	274.70	3850.55	50.64	62.69
Ghana		1993	no	0.11	0.17	1.32	0.03	0.02
Greece	yes	1988	1996	0.51	0.63	4.76	0.05	0.06
Guatemala		1996	no	0.09	0.14	2.59	0.02	0.02
Honduras	yes	1988	no	0.12	0.12	1.05	0.02	0.02
Hong Kong		1991	1994	2.92	3.33	49.81	0.55	0.60
Hungary		1994	1995	5.54	5.97	12.41	0.24	0.29
Iceland	yes	1989	no	0.30	0.42	6.30	0.05	0.06
India		1992	1998	3.52	3.19	91.19	0.44	0.71
Indonesia		1991	1996	0.15	0.21	1.83	0.02	0.04
Iran		no	no	0.18	0.26	2.75	0.03	0.03
Ireland	yes	1990	no	4.26	4.99	72.32	0.45	0.55
Israel	yes	1981	1989	9.88	12.24	395.18	2.36	2.43
Italy	yes	1991	1996	86.15	85.30	410.45	5.92	6.80
Jamaica		1993	no	0.09	0.13	1.68	0.02	0.01

Japan	yes	1988	1990	468.34	257.73	9619.70	112.22	103.77
Jordan		no	no	0.23	0.22	2.07	0.03	0.05
Kazakhstan		1996	no	0.10	0.15	0.28	0.01	0.02
Kenya		1989	no	0.12	0.12	1.22	0.02	0.03
Kuwait		no	no	0.18	0.23	1.82	0.04	0.04
Latvia		no	no	0.17	0.25	0.89	0.01	0.02
Lebanon		1995	no	0.13	0.15	1.72	0.02	0.02
Lithuania		1996	no	0.11	0.15	1.38	0.02	0.02
Luxembourg	yes	1991	no	2.34	2.54	24.22	0.32	0.40
Macedonia		1997	no	0.12	0.12	0.66	0.00	0.03
Malaysia		1973	1996	0.62	0.78	13.84	0.11	0.15
Malta		1990	no	0.23	0.29	2.61	0.03	0.05
Mauritius		1988	no	0.13	0.14	2.61	0.01	0.03
Mexico	yes	1975	no	2.35	2.74	13.75	0.18	0.21
Moldova		1995	no	0.11	0.09	0.21	0.02	0.03
Morocco		1993	no	0.11	0.16	0.66	0.02	0.02
Netherlands	yes	1989	1994	42.22	38.18	537.43	5.77	7.10
New Zealand		1988	no	1.28	1.81	25.48	0.26	0.27
Nigeria		1979	no	0.12	0.14	1.17	0.02	0.02
Norway	yes	1985	1990	8.06	10.10	69.34	0.94	1.20
Oman		1989	1999	0.06	0.06	0.40	0.01	0.02
Pakistan		1995	no	0.11	0.14	1.17	0.02	0.03
Panama		1996	no	0.34	0.38	3.38	0.05	0.05
Paraguay		1999	no	0.06	0.08	0.56	0.01	0.01
Peru		1991	1994	0.12	0.16	1.21	0.03	0.02
Philippines		1982	no	0.16	0.22	2.72	0.03	0.03
Poland	yes	1991	1993	37.14	38.93	7.88	0.09	0.14
Portugal	yes	1986	no	1.23	1.51	3.34	0.06	0.10
Romania		1995	no	0.26	0.33	2.91	0.04	0.04
Russia		1996	no	2.06	2.78	32.35	0.35	0.43
Saudi Arabia		1990	no	0.42	0.48	11.36	0.10	0.12
Singapore		1973	1978	4.00	3.62	121.64	0.81	1.00
Slovakia	yes	1992	no	1.30	1.59	1.88	0.03	0.06
Slovenia	yes	1994	1998	2.99	3.65	5.27	0.10	0.17
South Africa		1989	no	2.11	2.90	28.08	0.42	0.46
South Korea	yes	1976	1988	324.62	119.60	1625.85	16.48	18.93
Spain	yes	1994	1998	34.54	38.09	89.86	1.16	3.20
Sri Lanka		1987	1996	0.10	0.16	1.81	0.02	0.02
Swaziland		no	no	0.05	0.05	0.06	0.00	.
Sweden	yes	1971	1990	42.85	42.83	538.11	5.73	6.46
Switzerland	yes	1988	1995	46.22	45.41	554.29	6.87	7.54
Tanzania		1994	no	0.10	0.13	0.42	0.03	0.02
Thailand		1984	1993	0.30	0.39	7.47	0.06	0.06
Trinidad and Tobago		1981	no	0.11	0.14	1.09	0.02	0.02
Tunisia		1994	no	0.11	0.16	0.68	0.01	0.01
Turkey	yes	1981	1996	0.96	1.01	7.52	0.06	0.11
Ukraine		no	no	0.29	0.40	4.48	0.04	0.06
United Kingdom	yes	1980	1981	84.58	93.94	1147.26	14.34	16.50
United States	yes	1934	1961	1273.62	955.32	35387.68	321.29	311.78
Uruguay		1996	no	0.15	0.19	1.27	0.01	0.02
Uzbekistan		no	no	0.10	0.12	0.17	0.01	0.02
Venezuela		1998	no	0.51	0.53	5.11	0.12	0.12
Zimbabwe		no	no	0.07	0.10	0.73	0.02	0.01

Table 1 Summary Statistics

This table presents the unweighted summary statistics across all the industry-country-year observations within the sample period 1976-2006. *Patent Count** is defined as the total number of eventually-granted patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities** is the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation** is the total number of citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and Originality** are the sum of the generality and originality scores of all the patents in industry *i* that are filed in year *t* by applicants from country *c* respectively. *Patent Count*, *Patent Entities*, *Citation*, *Generality* and *Originality* are the natural logarithm of one plus the respective values of *Patent Count**, *Patent Entities**, *Citation**, *Generality**, and *Originality**. We restrict to patents filed and granted by the patent offices in one of the 34 OECD countries and/or EPO and we work with patent families to define patent-based measures of innovation. Country-level characteristics cover economic development (*GDP*, *GDP per capita*, both in natural logarithm), equity/credit market development (*Stock/GDP*, *Credit/GDP*), each industry's share of its country's export to the U.S. (*Export to US*) and legal origins (*UK Origin*, *FRSP Origin*, *SCAN Origin*, *GER Origin*). Industry-level variables consist of a series of U.S.-based industry indicators representing different natural rate of innovation (*High Tech*, *Innovation Propensity* and *MTB*) and information opacity (*Intangibility* and *STD of MTB*). Industry-level equity issuance activities include the number of equity issuance (*IPO Number*, *SEO Number* and *Total Issue Number*), total proceeds from equity issuance (*IPO Proceeds*, *SEO Proceeds* and *Total Proceeds*) and proceeds per issuance (*Proceeds per IPO*, *Proceeds per SEO* and *Proceeds per Issue*), respectively measured for total equity issuance (both IPO and SEO), IPO and SEO, which are all transformed into the natural logarithm of one plus the original value. Appendix Table A1 provides detailed definitions of the variables.

Statistics	N	10th Percentile	Mean	Median	90th Percentile	Std. Dev.
Patent-Based Innovation Measures						
Patent Count*	76,321	0.0223	35.8805	0.8617	54.4449	203.9964
Patent Entities*	76,321	0.0306	27.0447	1.0765	54.0415	109.6014
Citation*	76,321	0.0265	441.6349	4.9310	426.4162	3,525.6150
Generality*	70,684	0	5.5685	0.1092	6.7693	34.9607
Originality*	72,111	0	5.9917	0.1185	7.6737	37.3076
Patent Count	76,321	0.0221	1.3911	0.6215	4.0154	1.6643
Patent Entities	76,321	0.0301	1.4375	0.7307	4.0081	1.6190
Citation	76,321	0.0261	2.4735	1.7802	6.0578	2.3948
Generality	70,684	0	0.6048	0.1037	2.0502	1.0425
Originality	72,111	0	0.6300	0.1120	2.1603	1.0694
Economic Development						
Credit/GDP	70,515	0.3023	0.8029	0.7128	1.4037	0.4911
GDP	74,121	22.8105	25.1663	25.3273	27.2977	1.6885
GDP per capita	74,080	7.0837	8.7706	8.9458	10.2619	1.2527
Export to US	76,321	0	0.0207	0	0.0534	0.0706
Stock/GDP	74,121	0	0.3427	0.1272	0.9958	0.5372
Legal Environment						
FRSP Origin	50,983	0	0.4250	0	1	0.4944
GER Origin	50,983	0	0.1419	0	1	0.3489
SCAN Origin	50,983	0	0.1139	0	1	0.3177
UK Origin	50,983	0	0.3192	0	1	0.4662
Industry Groups (Dummies)						
High Tech	73,410	0	0.4831	0	1	0.4997
Illiquidity	76,321	0	0.4938	0	1	0.5000
Innovation Propensity	73,219	0	0.4848	0	1	0.4998
Intangibility	76,321	0	0.4925	0	1	0.4999
MTB	76,321	0	0.4892	0	1	0.4999
STD of MTB	75,059	0	0.4817	0	1	0.4997

Industry Equity Issuance						
IPO Number	76,321	0	0.0712	0	0	0.3285
IPO Proceeds	76,321	0	0.2081	0	0	0.9321
Proceeds per IPO	76,321	0	0.1669	0	0	0.7545
Proceeds per Issue	76,321	0	0.2968	0	0	1.0179
Proceeds per SEO	76,321	0	0.2074	0	0	0.8704
SEO Number	76,321	0	0.0836	0	0	0.3701
SEO Proceeds	76,321	0	0.2579	0	0	1.0731
Total Issue Number	76,321	0	0.1306	0	0	0.4721
Total Proceeds	76,321	0	0.3819	0	0	1.2984

Table 2 Timing of Insider Trading Law Enforcement and Pre-existing Innovation: Hazard Model Estimation

This table shows the estimated effect of country-level patent-based measures of innovation before the initial enforcement of the insider trading laws on the expected time to the initial enforcement based on Weibull distribution of the hazard rate. *Patent Count*^{c} is the natural logarithm of one plus the total number of eventually-granted patent applications filed in year *t* by applicants from country *c*. *Patent Entities*^{c} is the natural logarithm of one plus the total number of distinct entities in country *c* that apply for patents in year *t*. *Citation*^{c} is the natural logarithm of one plus the total number of citations to patent families in country *c*, and in year *t*, where *t* is the application year. *Generality*^{c} and *Originality*^{c} are the natural logarithm of one plus the sum of the generality and originality scores of all the patents that are filed in year *t* by applicants from country *c*, respectively. Only counties whose initial enforcement of insider trading laws is within the sample period 1976-2006 are included in the regression analyses and they drop out of the sample once the law is enforced. Control variables are grouped into economic development and legal environment. Measurements of economic development include *GDP*, *GDP per capita*, *Stock/GDP* and *Credit/GDP*. Measurements of legal environment include three dummies for legal origins: *UK Origin*, *FRSP Origin*, *GER Origin*, indicating UK origin, French and Spanish origin as well as Germany origin respectively, whereas *SCAN Origin* (i.e., Scandinavian origin) serves as the base group. Appendix Table A1 provides detailed definitions of the variables. Robust z-statistics are reported in parenthesis, which are based on standard errors clustered at country level. ***, **, * denote significance levels at 1%, 5% and 10% respectively. The Wald test of joint significance of the five patent-based measures of innovation and the corresponding p-value is presented in the bottom two rows.

Patent-based measures included simultaneously

Dependent variable	ln(survival time)		
	(1)	(2)	(3)
Patent Count^c	-0.1626	-0.2912	-0.4123
	(-1.33)	(-1.37)	(-0.57)
Patent Entities^c	0.1904	0.3136	0.7684
	(1.42)	(1.33)	(1.36)
Citation^c	-0.2903	-0.2977	-0.3444
	(-1.61)	(-1.46)	(-0.99)
Generality^c	0.2561	0.3138	0.6857
	(0.98)	(1.00)	(1.10)
Originality^c	0.0333	0.0194	-0.4827
	(0.26)	(0.11)	(-0.71)
Economic Controls	No	Yes	Yes
Legal Controls	No	No	Yes
Observations	524	473	436
Wald Test Statistic	8.17	5.18	3.25
P-value of Wald Test	0.1471	0.3940	0.6621

Table 3 Insider Trading Law Enforcement and Innovation: Baseline

This table presents the baseline panel regression results of the initial enforcement of insider trading laws on the innovation activities measured at the industry-country level using the following specification: $\text{Innovation}_{i,c,t} = \alpha_0 + \alpha_1 \text{Enforce}_{c,t} + \gamma X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$. *Enforce* is the key explanatory variable, which is equal to one for years after the law is enforced for the first time in a country. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c* that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Panel A

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
Enforce	0.3088**	0.2515**	0.3702**	0.1656***	0.2332***
	(2.44)	(2.25)	(2.39)	(2.70)	(3.47)
Controls	No	No	No	No	No
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	76,321	76,321	76,321	70,684	72,111
Adjusted R-squared	0.846	0.860	0.849	0.771	0.776

Panel B

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(6)	(7)	(8)	(9)	(10)
Enforce	0.2594**	0.2061**	0.3666***	0.1584***	0.1809***
	(2.19)	(2.04)	(2.67)	(2.80)	(2.93)
Controls	Yes	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	70,319	70,319	70,319	65,641	67,014
Adjusted R-squared	0.858	0.873	0.863	0.781	0.788

Table 4 Insider Trading Law Enforcement and Innovation: By Industry High-tech Intensiveness

This table shows the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different high-tech intensiveness. We use the following specification: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{High Tech}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *High Tech* is a dummy variable set equal to one if the measurement of high-tech intensiveness at the two-digit SIC is above the sample median and zero otherwise; High-tech intensiveness is defined as the average growth rate of R&D expense over the sample period in each industry benchmarked to the U.S. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP, GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
High Tech×Enforce	0.4283***	0.3729***	0.4293***	0.4240***	0.4212***
	(6.28)	(6.73)	(6.37)	(5.37)	(5.62)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	73,410	73,410	73,410	68,010	69,403
Adj. R-squared	0.894	0.905	0.898	0.811	0.823

Table 5 Insider Trading Law Enforcement and Innovation: By Industry Innovation Propensity

This table shows the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different innovation propensity. We use the following specification: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{Innovation Propensity}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *Innovation Propensity* is a dummy variable set to one if the measurement of innovation propensity at the two-digit SIC is above the sample median and zero otherwise; innovation propensity is defined as the average number of patents filed by a U.S. firm in a particular industry over the sample period. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count (1)	Patent Entities (2)	Citation (3)	Generality (4)	Originality (5)
Innovation Propensity×Enforce	0.5029***	0.4570***	0.4501***	0.5255***	0.5222***
	(6.47)	(6.76)	(6.26)	(5.45)	(5.66)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	73,219	73,219	73,219	67,856	69,242
Adj. R-squared	0.895	0.905	0.898	0.813	0.824

Table 6 Insider Trading Law Enforcement and Innovation: By Industry Growth Potential

This table demonstrates the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different growth potential. The regression specification follows: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{MTB}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *MTB* is a dummy variable set to one if the MTB at the two-digit SIC is above the sample median and zero otherwise; industry MTB is measured as average market-to-book equity ratio of each industry benchmarked to the U.S. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
MTB×Enforce	0.1499***	0.1156***	0.1419***	0.1983***	0.1923***
	(4.52)	(4.11)	(3.56)	(5.28)	(5.41)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	76,321	76,321	76,321	70,684	72,111
Adj. R-squared	0.891	0.902	0.895	0.802	0.814

Table 7 Insider Trading Law Enforcement on Innovation: By Industry Asset Intangibility

This table demonstrates the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different proportion of intangible assets. The specification follows: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{Intangibility}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *Intangibility* is a dummy variable set to one if intangibility measurement at the two-digit SIC is above the sample median and zero otherwise; we measure intangibility as one minus PPE/Asset ratio of each industry benchmarked to the U.S. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is defined as the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
Intangibility×Enforce	0.2961***	0.2638***	0.2648***	0.2639***	0.2715***
	(6.89)	(7.15)	(5.75)	(5.68)	(6.03)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	76,321	76,321	76,321	70,684	72,111
Adj. R-squared	0.892	0.903	0.896	0.803	0.815

Table 8 Insider Trading Law Enforcement and Innovation: By Industry Valuation Dispersion

This table demonstrates the differential effects of the enforcement of insider trading law on the innovative activities across industries that are characterized with different extent of valuation dispersion. The regression specification follows: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{STD of MTB}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *STD of MTB* is a dummy variable set to one if the standardized valuation dispersion at the two-digit SIC is above the sample median and zero otherwise; it is measured as the standard deviation of market-to-book equity ratio over the average market-to-book equity ratio within each industry benchmarked to the U.S. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
STD of MTB×Enforce	0.2051***	0.1627***	0.2234***	0.2869***	0.2796***
	(5.03)	(4.29)	(4.34)	(5.64)	(5.84)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	75,059	75,059	75,059	69,551	70,963
Adj. R-squared	0.893	0.905	0.897	0.810	0.822

Table 9 Insider Trading Law Enforcement and Innovation: By Industry Liquidity

This table shows the differential effects of the enforcement of insider trading laws on the innovative activities across industries with different market liquidity. The specification follows: $\mathrm{Innovation}_{i,\mathrm{c,t}} = \beta_0 + \beta_1 \mathrm{Enforce}_{\mathrm{c,t}} \times \mathrm{Illiquidity}_i + \lambda X'_{i,c,t} + \delta_{\mathrm{c,t}} + \delta_{i,\mathrm{t}} + \varepsilon_{i,\mathrm{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. *Illiquidity* is set equal to one if the Amihud illiquidity measurement of the corresponding U.S. industry at the two-digit SIC level is above the sample median and zero otherwise. The dependent variable, *Innovation*, is one of the five patent-based measures of innovation. *Patent Count* is the natural logarithm of one plus the total number of patent applications belonging to industry *i* that are filed in year *t* by applicants from country *c*. *Patent Entities* is the natural logarithm of one plus the total number of distinct entities in country *c*, that apply for patents in industry *i* in year *t*. *Citation* is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of either the generality or originality score of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Appendix Table A1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at the country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)
Illiquidity×Enforce	0.0141	-0.0028	0.0073	-0.0106	-0.0049
	(0.98)	(-0.26)	(0.36)	(-0.90)	(-0.42)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observation	76,321	76,321	76,321	70,684	72,111
Adj. R-squared	0.890	0.902	0.895	0.800	0.812

Table 10 Heterogeneous Impact of Insider Trading Law Enforcement on Equity Issuance

This table lays out the effect of the enforcement of insider trading laws on equity issuance activities at industry-country level, where industries are differentiated by the natural extent of innovation. We examine total equity issuance and specific types of equity issuance, namely, initial public offering (IPO) and seasoned equity offering (SEO) or the two activities combined, following the specifications: $\text{Equity Issuance}_{i,\text{c,t}} = \beta_0 + \beta_1\text{Enforce}_{\text{c,t}} \times \text{High Tech}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ and $\text{Equity Issuance}_{i,\text{c,t}} = \beta_0 + \beta_1\text{Enforce}_{\text{c,t}} \times \text{Innovation Propensity}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ in Panels A and B respectively. The dependent variable takes the natural logarithm of one plus the number, proceeds or proceeds per deal of equity issuance via IPO, SEO or the two activities combined (total) respectively in an industry-country-year. *Enforce* is a dummy variable set equal to one for years after the law is enforced for the first time in a country. Control variable is *Export to US* and other characteristics are subsumed by the country-year dummies $\delta_{\text{c,t}}$ and industry-year dummies $\delta_{i,\text{t}}$. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at country and industry level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Panel A

Dependent variables	IPO Number	IPO Proceeds	Proceeds per IPO	SEO Number	SEO Proceeds	Proceeds per SEO	Total Issue Number	Total Proceeds	Proceeds per Issue
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Tech×Enforce	0.1022***	0.2650***	0.1884***	0.1305***	0.3237***	0.2191***	0.1690***	0.3969***	0.2542***
	(4.24)	(4.29)	(4.42)	(4.78)	(4.95)	(4.60)	(5.00)	(5.18)	(4.96)
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,410	73,410	73,410	73,410	73,410	73,410	73,410	73,410	73,410
Adj. R-squared	0.388	0.319	0.285	0.416	0.333	0.278	0.482	0.402	0.338

Panel B

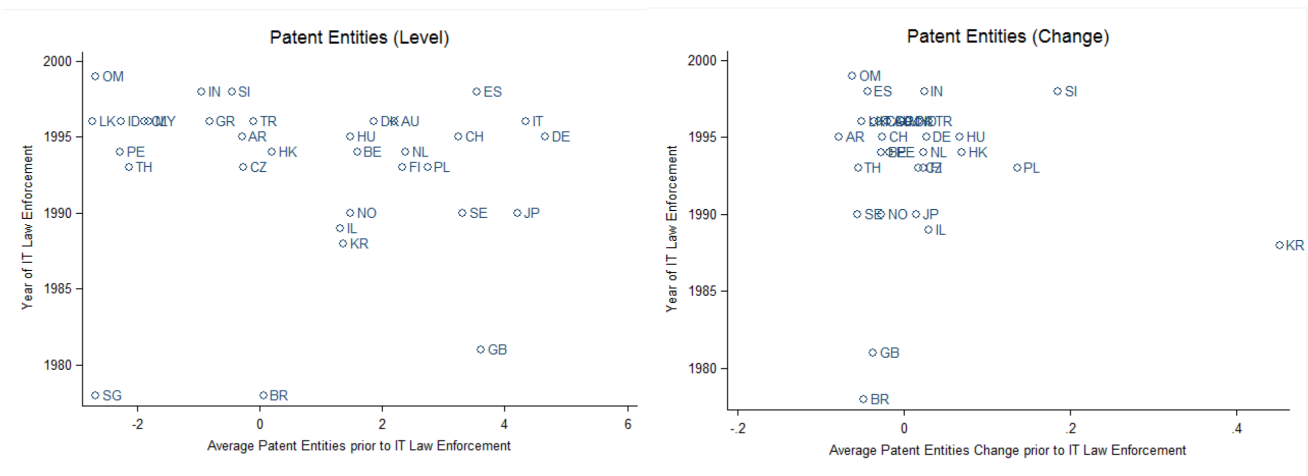
Dependent variables	IPO Number	IPO Proceeds	Proceeds per IPO	SEO Number	SEO Proceeds	Proceeds per SEO	Total Issue Number	Total Proceeds	Proceeds per Issue
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Innovation Propensity × Enforce	0.1447***	0.3761***	0.2682***	0.1938***	0.5163***	0.3605***	0.2476***	0.6289***	0.4196***
	(3.89)	(4.89)	(4.01)	(4.79)	(5.39)	(5.66)	(4.94)	(5.43)	(5.66)
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,219	73,219	73,219	73,219	73,219	73,219	73,219	73,219	73,219
Adj. R-squared	0.389	0.321	0.287	0.418	0.338	0.282	0.484	0.407	0.343

Figure 1. Timing of Insider Trading Law Enforcement and Pre-existing Innovation

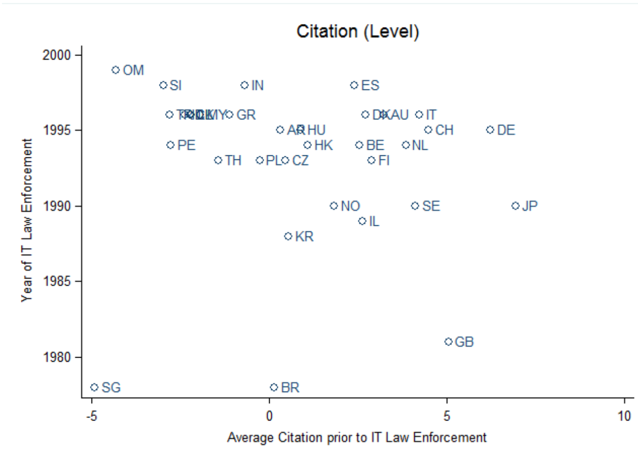
The set of figures plot the average level of innovation and the average rate of change in innovation before the initial enforcement of the insider trading laws against the year of the initial enforcement. Innovation takes one of the five patent-based measures of innovation at country level: *Patent Count*^{c}, *Patent Entities*^{c}, *Citation*^{c}, *Generality*^{c} and *Originality*^{c} respectively. Appendix Table A1 provides detailed definitions of the variables. Only countries with enforcement of insider trading laws within our sample period 1976-2006 are plotted in the figures.

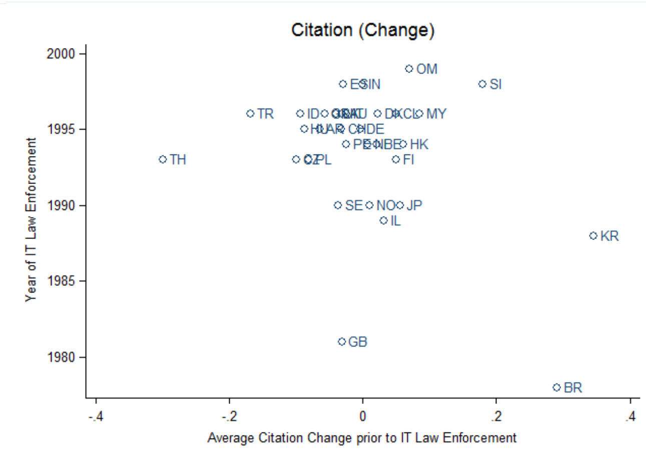
(1) Patent Count

(2) Patent Entities



(3) Citation





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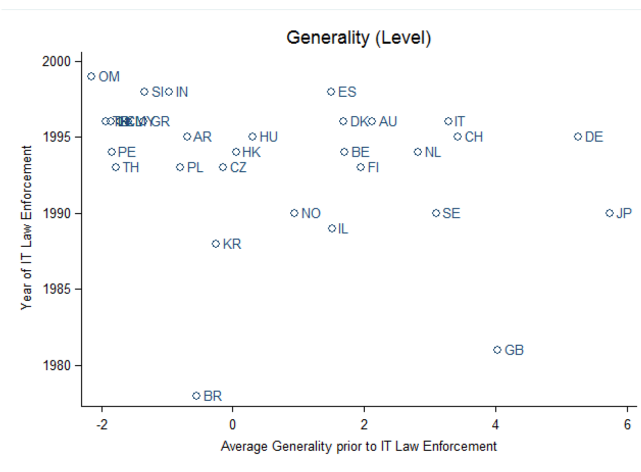

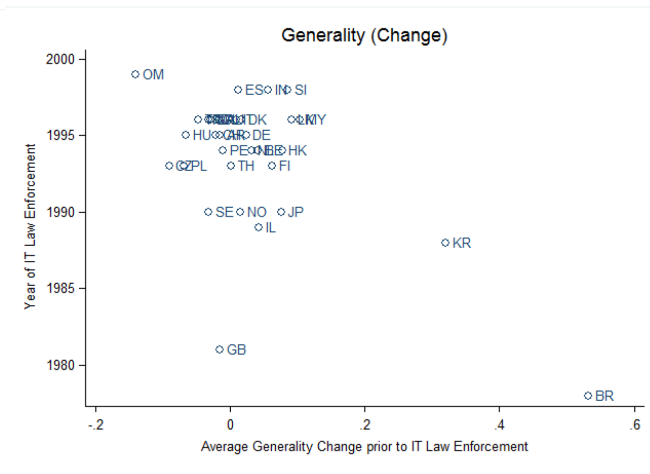

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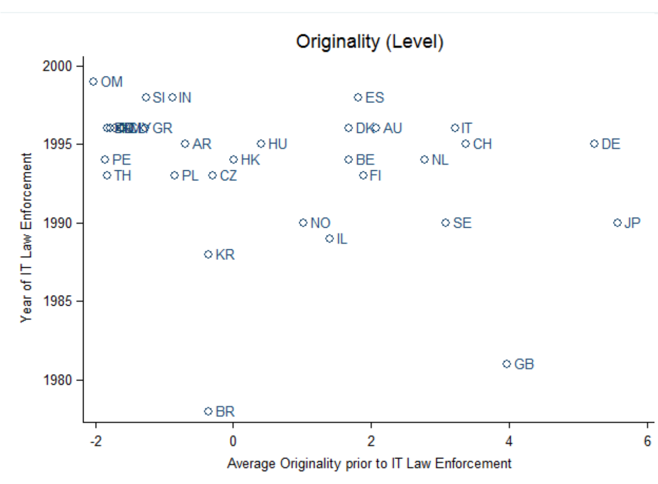
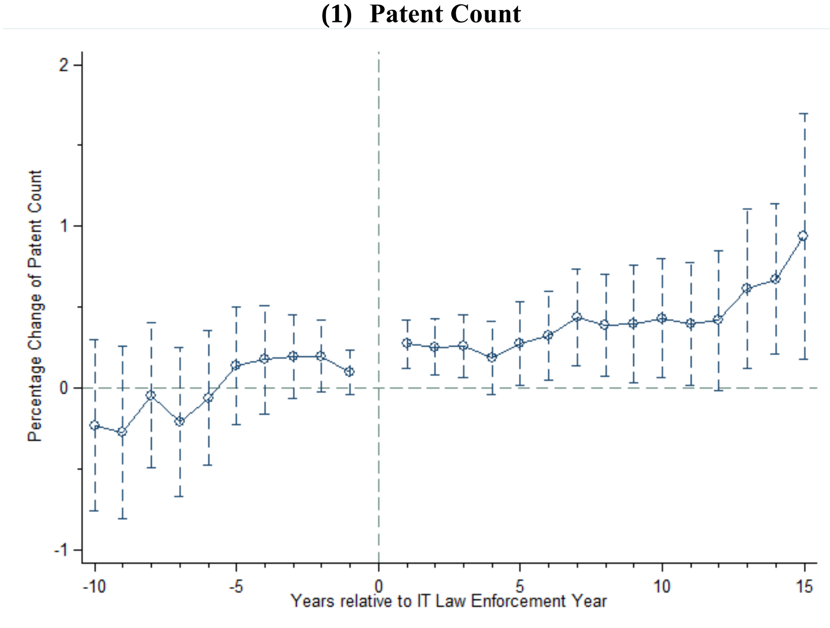


Figure 2. Dynamics of Insider Trading Law Enforcement and Innovation

The figures plot the dynamic impact of the enforcement of insider trading laws on innovative activities. We use the following specification: $\text{Innovation}_{c,t} = \alpha_0 + \alpha_{1,\tau} \sum_{\tau=t-10}^{\tau=t+15} \text{Enforce}_{c,\tau} + \lambda X'_{c,t} + \delta_c + \delta_t + \varepsilon_{c,t}$. *Innovation* takes one of the five patent-based measures of innovation at country level respectively: *Patent Count* [c], *Patent Entities* [c], *Citation* [c], *Generality* [c] and *Originality* [c]. Control variables include *GDP*, *GDP per capita*, *Stock/GDP* and *Credit/GDP*. Appendix Table A1 provides detailed definitions of the variables. A 25-year window spanning from 10 years before to 15 years after the year of initial enforcement is used in the estimation, with country and year fixed effects included. The dotted lines represent the 95% confidence interval of the estimated effect where standard errors are clustered at the country level. The year of initial enforcement is excluded and serves as the benchmark year. The figures are centered on the year of enforcement.

(1) Patent Count



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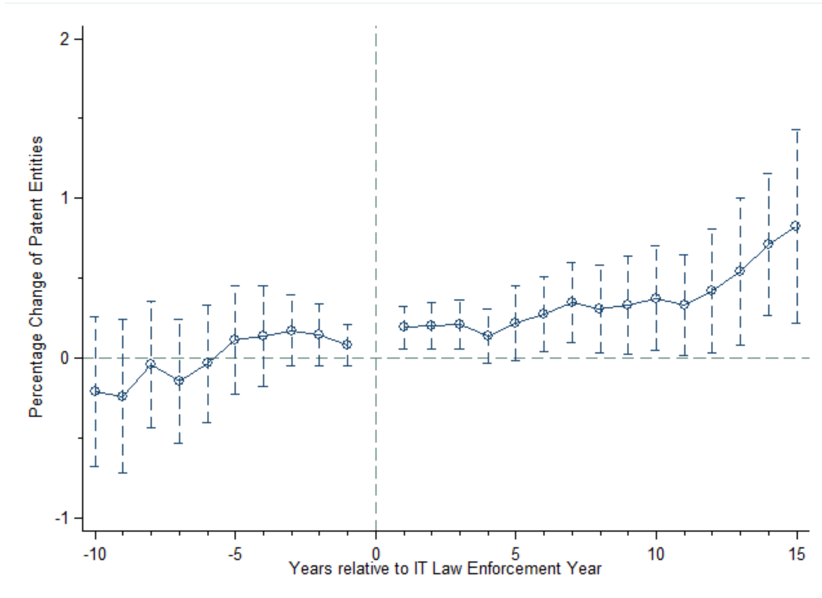

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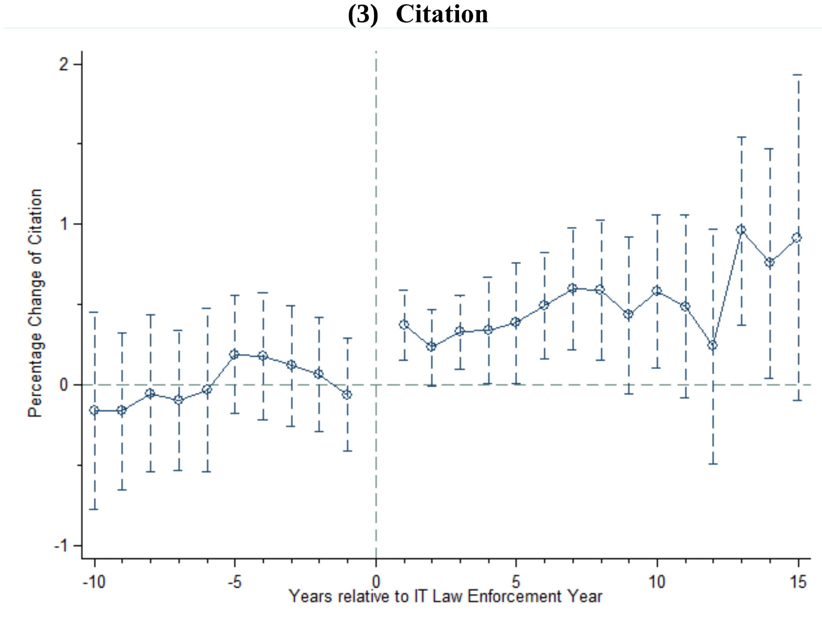

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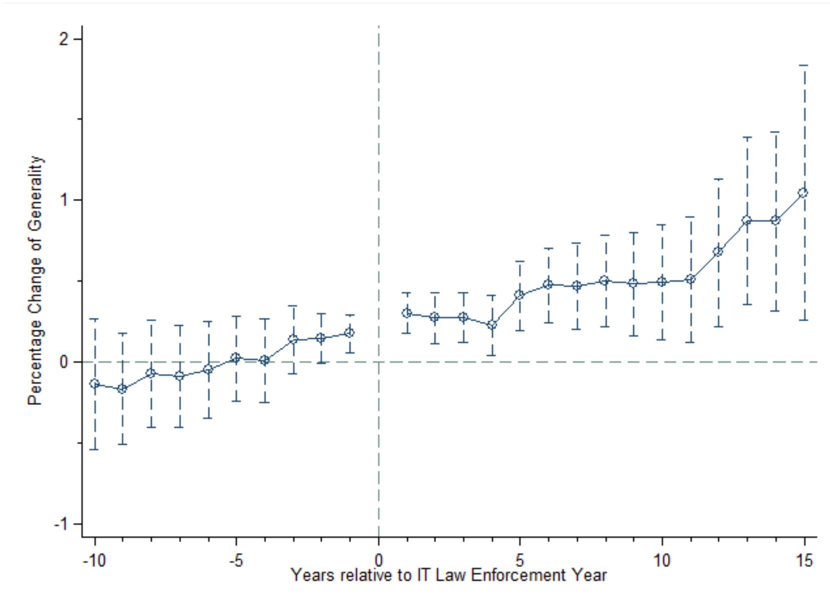
Percentage Change of Generality
2
1
0
-1
-10
-5
0
5
10
15
Years relative to IT Law Enforcement Year

(5) Originality