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INSIDER TRADING AND INNOVATION

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Abstract

This paper assesses whether legal systems that protect outside investors from corporate insiders increase or decrease the rate of technological innovation. Based on over 75,000 industry-country-year observations across 94 economies from 1976 to 2006, we find that enforcing insider trading laws spurs innovation—as measured by patent intensity, scope, impact, generality, and originality. 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, and equity issuances also rise much more in these industries after a country starts enforcing its insider trading laws.

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

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1. Introduction

The finance and growth literature emphasizes that financial markets shape economic growth primarily by boosting productivity growth (e.g., King and Levine, 1993a, b, Levine and Zervos, 1998, Rajan and Zingales, 1998, Beck et al., 2000 and Levine, 2005), and this literature has recently found a strong link between finance and the rate of technological innovation (Amore et al., 2013, Chava et al., 2013, Fang et al., 2014, Hsu et al., 2014, Acharya and Xu, 2015 and Laeven et al., 2015). Partially motivated by research on finance and growth, the law and finance literature stresses that legal systems that protect the voting rights of minority shareholders and limit the ability of large shareholders and executives to expropriate corporate resources through self-dealing transactions enhance financial markets (e.g., La Porta et al., 1997, 1998, 2002, 2006 and Djankov et al., 2008). What these literatures have not yet addressed is whether legal systems that protect outside investors from corporate insiders influence a crucial source of economic growth—technological innovation. In this paper, we focus on one such protection. We examine whether restrictions on insider trading—trading by corporate officials, major shareholders, or others based on material non-public information—influences technological innovation.

Theory offers differing perspectives on whether restricting insider trading would accelerate or slow innovation. One set of theories suggests that restricting insider trading enhances the valuation of and hence improves investments in technological innovation. This view builds from the premise that technological innovation is difficult for outside investors to evaluate (e.g., Holmstrom, 1989, Allen and Gale, 1999), so that improving incentives for acquiring information enhances valuations, lowers the cost of capital, and improves investment in innovative activities (Merton, 1987, Diamond and Verrecchia, 2012). One way that restricting insider trading can increase incentives for acquiring information is by reducing the ability of corporate insiders to exploit other investors, which encourages those investors to devote more resources to valuing firms and improves the informativeness of stock prices, as modeled by Fishman and Hagerty (1992) and DeMarzo et al. (1998) and shown empirically by Bushman et al. (2005) and Fernandes and Ferreira (2009). Another way that restricting insider trading can improve valuations is by boosting market liquidity

(Bhattacharya and Doauk, 2002). Greater liquidity can make it less costly for investors who have acquired information to profit by trading in public markets (Kyle, 1984), which encourages investors to devote more resources toward collecting information (Holmstrom and Tirole, 1993). Furthermore, market liquidity can facilitate arbitrage trading activities and correct the pricing of mis-valued stocks (Chordia, Roll, and Subrahmanyam, 2008). Thus, restricting insider trading can improve the valuation of and enhance investment in innovation.

Other theories, however, suggest that restricting insider trading can deter effective price discovery, with adverse effects on innovation. For example, Leland (1992) stresses that insider trading quickly reveals that information in public markets, improving the informativeness of prices and the allocation of resources. And, Grossman and Stiglitz (1980) argue that when liquid markets immediately reveal information to the public, this reduces the incentives for investors to expend private resources acquiring information on firms. From these perspectives, restricting insider trading could slow innovation by increasing informational asymmetries about novel endeavors.

By influencing price discovery and market liquidity, insider trading can also affect managerial incentives. To the extent that restricting insider trading enhances the efficiency of stock prices, this can reduce the disincentives of investing in opaque and risky, albeit value-maximizing, innovative endeavors, as suggested by the work of Manso (2011), Ederer and Manso (2013), and Ferreira et al. (2014). In contrast, highly liquid markets can both (a) attract myopic investors who chase short-run profits (e.g., Bushee, 1998, 2001), which can incentivize managers to forgo profit-maximizing long-run investments in order to satisfy short-term performance targets (Stein, 1988, 1989) and (b) facilitate takeovers (Kyle and Vila, 1991), which can encourage managers to choose investments that boost short-run profits instead of longer gestation investments in innovation (Shleifer and Summers, 1988). Thus, theory suggests that restricting insider trading can either enhance or harm managerial incentives, with correspondingly conflicting predictions about the impact of insider trading on innovation.

To provide the first assessment of whether legal systems that protect outside investors from corporate insiders increase or decrease the rate of innovation, we exploit the quasinatural experiment of the staggered enforcement of insider trading laws across countries. Specifically, we use the date when a country first prosecutes a violator of its insider trading laws, which is provided by Bhattacharya and Daouk (2002) for 103 countries starting with the U.S. in 1961. This setting is appealing for three reasons. First, countries started enforcing their insider trading laws for a variety of reasons, such as increased competition between stock exchanges for trading volume, and differences in political ideologies (Beny, 2013). Fortunately, there is no indication that technological innovation or the desire to influence innovation affected the timing of when countries started enforcing their insider trading laws. Thus, the potential effects of enforcement on innovation are likely unintended consequences of these legal actions. Second, the cross-country heterogeneity in the timing of the enforcement of insider trading laws allows us to employ a difference-in-differences strategy to identify their impact on innovation. As discussed below, we conduct and report several tests that support the validity of this strategy. Third, this setting allows us to test whether the cross-industry response of innovation and equity issuances to restrictions on insider trading are consistent with particular theoretical perspectives of how insider trading affects innovation. For example, models stressing that insider trading discourages outside investors from researching firms predict that restricting insider trading will have a particularly positive impact on investment in informationally opaque activities, including innovation. By conducting these evaluations, we contribute to theoretical and policy debates about how legal systems that protect small investors influence on the rate of technological innovation.

We use patent-based measures of innovation. Specifically, we obtain information on patenting activities for industries (two-digit SIC level) in 94 countries from 1976 through 2006 from the EPO Worldwide Patent Statistical Database (PATSTAT) and compile a sample of 76,321 country-industry-year observations. We construct and examine five patent-based proxies for technological innovation, but focus on two—the number of patents and the number of patent citations—since they gauge the intensity and impact of innovative activity. We also study (a) the number of patenting entities to assess the scope of innovative activities (Acharya and Subramanian, 2009), (b) the degree to which technology classes other than the one of the patent cite the patent, and (c) the degree to which the patent cites innovations in other technology classes (Hall et al., 2001).

We begin with a simple difference-in-differences specification. Specifically, the patent-based proxies of innovation, which are measured at the country-industry-year level, are regressed on the enforcement indicator, which equals one after a country first enforces its insider trading laws and zero otherwise. The regression also includes country, industry, and year fixed effects and an assortment of time-varying country and industry characteristics. Since we are concerned that the size of the economy and the level of economic development might shape both innovation and policies toward insider trading, we control for Gross Domestic Product (GDP) and GDP per capita. Since stock market and credit conditions could influence innovation and the restrictions on insider trading, we also include stock market capitalization as a share of GDP and credit as a share of GDP. Finally, factors shaping the evolution of an industry's export could also confound the analyses, so we control for industry exports to the U.S. As mentioned above and described further below, we also examine theoretical predictions concerning the differential impact of insider trading across industries. Since we use U.S. data to categorize industries, we omit the U.S., though the results are robust to including it.

We find that (1) the enforcement of insider trading laws is associated with a material and statistically significant increase in each of the five proxies of innovation and (2) several tests support the validity of our econometric strategy. 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%. In assessing the validity of this approach, we first test and confirm that neither the level nor the growth rate in the patent-based measures predict the timing of the enforcement of insider trading laws. Second, we find no significant pre-trends in the patent-based measures of innovation before a country's first enforcement action. Rather, there is a notable upward break in the time-series of the innovation measures after a country starts enforcing its insider trading laws. Third, we employ a discontinuity approach and assess whether other factors, such as trade, credit, real output, etc. change in the same way after a country starts restricting insider trading as the patent-based indicators change. We find that they do not, advertising the link between insider trading and innovation per se. Fourth, we were concerned that other factors could be changing at the same time as the enforcement of insider trading, confounding our identification strategy. Consequently, we use a control function approach and include an array of policy changes associated with international capital flows, securities markets, and banks. Controlling for these policy reforms does not alter the results and has little effect on the estimated coefficients.

We next augment our approach to test whether the cross-industry response of innovation to restrictions on insider trading are consistent with particular theoretical perspectives of how insider trading shapes innovation. That is, we include an interaction term between the enforcement indicator and industry characteristics to examine the heterogeneous response of industry innovation to the enforcement of insider trading laws. In these industry-level analyses, we control for country-year and industry-year fixed effects to 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 time-varying industry characteristics that might confound our ability to draw sharp inferences about the relationship between insider trading and innovation. By focusing on changes in the cross-industry patterns of innovation, these analyses enhance the identification strategy and provide cleaner insights into the relationship between insider trading and innovation.

We differentiate industries along two theoretically-motivated dimensions. First, we distinguish 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 U.S. 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.

We find that the patent-based measures of innovation rise much more in naturally innovative and naturally opaque industries after a country starts enforcing its insider trading laws. For example, after a country's first prosecution of insider trading, the number of patents jumps 50% more in its industries that have above the median level of patenting activity in the U.S. than it rises in its industries with below the median values. The same is true when splitting the sample by the natural opacity of industries. For example, in industries with above the median levels of intangible assets in the U.S., the patent-based measures of innovation increase 30% more than they rise in industries with naturally lower levels of intangible assets. Thus, enforcement is associated with a material increase in patent-based measures of innovation and the cross-industry pattern of this increase is consistent with theories in which restricting insider trading improves the informational content of stock prices.

We further extend these analyses by examining equity issuances. One mechanism through which enhanced valuations can spur innovation is by lowering the cost of capital for investment in innovation. Consistent with this view, we find that both initial public offering (IPO) and seasonal equity offering (SEO) rise much more in naturally innovative industries than they do in other industries after a country first enforces its insider trading laws. In particular, the value of equity issuances increases 40% to 63% more in naturally innovative industries than it rises in other industries after a country starts enforcing its insider trading laws. These findings further support the view that legal systems that protect outside investors from corporate insiders facilitate investment in innovative activities.

We also address several potential additional concerns. First, the results might be driven only by the extensive margin, in which an industry in a country first applies for a patent, or the intensive margin, in which already innovating industries intensify their patenting activities. We find that innovation increases at both the extensive and intensive margins after countries start enforcing their insider trading laws. Second, we were concerned that the results might only obtain in some countries, so we split the sample by the level of economic development, the level financial development, and whether the country has a market-oriented political ideology. The results hold in each of these subsamples with very similar coefficient estimates.

Our findings relate to several lines of research. A considerable body of work finds that laws and regulations that protect small investors by enhancing the transparency, integrity, and contestability of markets enhance the quality of financial markets and institutions (e.g., La Porta et al., 2006, Barth et al., 2006). Consistent with these findings, we find that restricting insider trading is associated with a material increase in innovative activity and a sharp rise in equity issuances among firms in innovative industries. Similarly, our work contributes to the debate on the regulation and social consequences of insider trading (Fishman and Hagerty, 1992, Leland, 1992, Khanna et al., 1994, DeMarzo et al, 1998, Acharya and Johnson, 2007, 2010). Although we do not examine each theoretical channel through which insider trading might affect innovation, we do show that enforcing insider trading laws boosts innovation and equity issuances in a manner that is consist with models emphasizing that insider trading reduces the precision with which markets value innovative activities and raises the cost of capital for such investments.

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

In this section, we describe the data on the enforcement of insider trading laws and patents. We define the other data used in the analyses when we present the regression results.

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 these 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 year in which a country first prosecutes a violator of its insider trading laws, rather than the date on which a country first enacts laws restricting insider trading, 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), 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 provided in *Appendix A*, 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 U.S. 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 prosecutes somebody for violating 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 EPO 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 when the patent is granted, 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)).[1, 2]

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 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 has data through 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 European Patent Office (EPO) or by 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 U.S. as the benchmark economy when characterizing industry traits for all countries (Rajan and Zingales, 1998). To

[1] 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.

[2] 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 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.

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 U.S. This restriction excludes Zambia, Namibia, Botswana, and Mongolia. The results, however, are robust to including these countries or the U.S. 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.[3] 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.

Following the patent literature, we date patents using the application year of original 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, Acharya et al., 2013). 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 country of residence 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 of different patents within a patent family, by examining citations at the patent

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

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-country-year-level and merge different data sources, we must reconcile the different industrial classifications used by the PATSTAT and the other data sources and implement criterion for including or excluding industry-country-year observations in which we find no evidence of patenting activity. With respect to industry categories, we convert the PATSTAT IPCs into two-digit Standard Industrial Classifications (SICs).[4] With respect to sampling criteria, our core sample excludes an industry-country-year observation in which no entity in that country's industry files for a patent in that year. Thus, our core analyses focus exclusively on the intensive margin: Is there a change in patenting activity in industries already engaged in innovation? In robustness tests reported below, however, we also consider the extensive margin. We include those industry-country-year observations in which we find no patenting activity and code those observations as zero. All of the results hold when examining this large sample.

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

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-

[4] 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.

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 the method developed by Hall et al. (2001, 2005).[5] 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*.

[5] 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 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

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 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 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.[6]

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. Furthermore, we also create country-year aggregates of the patent-based measures of innovation, in addition to the country-industry-year versions discussed above.

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.

[6] *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.

For example, *Patent Count*^{c} equals the natural logarithm of one plus the total number of eventually-granted patent applications in year *t* by applicants from country *c*. *Patent Entities*^{c}, *Citation*^{c}, *Generality*^{c}, and *Originality*^{c} are defined analogously.

Table 1 and *Table 2* provide detailed variable definitions and summary statistics, respectively, on all of the variables used in the paper, while *Appendix A* provides more detailed information on the five patent-based indicators. In *Appendix A*, the patent-based measures 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 2* further emphasizes the large dispersion in innovation across countries by pooling overall industry-country-years. On average, a country-industry has 36 eventually-granted patents per year, while the standard deviation is as high as 204. *Citation** is also highly dispersed. In an average industry-country-year, the average value of *Citation** is 442 with a standard deviation of 3,526.

3. Empirical strategies

3.1 Baseline strategy

We begin with a standard difference-in-differences specification to assess whether patent-based indicators of innovation rise after a country first prosecutes a violator of its insider trading laws.

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

$Innovation_{i,c,t}$ 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. We use two-way clustering of the errors, at both the country and year level.

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 the size of the economy and the level of economic development might influence both legal approaches to insider trading and the degree to which entities file patents with patent offices in more developed OECD countries (Acharya and Subramanian 2009, Acharya et al., 2013). We also control for stock market capitalization (*Stock*/*GDP*) and domestic credit provided by the financial sector (*Credit*/*GDP*) since the overall functioning of the financial system can influence both innovation and the enforcement of insider trading laws. 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*), since economic linkages with the U.S. might shape an industry's investment in innovation. 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 indicators after the country first enforces its insider trading laws, conditioning on the various fixed effects and other control variables specified in equation (1). As shown below, the results are robust to including or excluding the time-varying country and industry characteristics (*X*).

There are several challenges, however, that we must address to use the coefficient estimate, α_1, to draw inferences about the impact of insider trading laws on the patent-based indicators of innovation. First, reverse causality could confound our analyses, i.e., the rate of innovation, or changes in the rate of innovation, might influence when countries enact and enforce their insider trading laws. Second, the patent-based indicators might be trending, so finding patenting activity is different after enforcement might reflect these trends, rather than a change associated with the enforcement of insider trading laws. Third, omitted variables might limit our ability to identify the impact of change in the legal system's protection of potential outside investors from corporate insiders on innovation. For example, 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 on innovation from α_1.

We address each of these concerns below. First, we find no evidence that either the level or the rate of change in the patent-based measures predict the timing of when countries start enforcing their insider trading laws. Second, we find no pre-trends in the patent-based indicators before a country's first enforcement action; rather there is a notable break in innovation after a country starts enforcing its insider trading laws. Third, we provide different assessment of the degree to which omitted variables affect the analyses: (1) we use a discontinuity design and test whether other factors, such as international trade and financial development, change in the same way that the patent-based indicators change after the enforcement of insider trading laws; (2) we include an array of other policy changes associated with international capital flows, trade, securities markets, and banks to assess the robustness of the estimated value of α_1; and (3) we augment the baseline strategy and assess the differential response of industries to the enforcement of insider trading laws, so that we can include country-year fixed effects to absorb any confounding events arising at the country-year level. As documented below, the evidence from these tests supports the validity of our econometric strategy.

3.2. Industry-based empirical strategy

We next assess whether the cross-industry response to enforcing insider trading laws is consistent with particular theoretical perspectives on how protecting outside investors from corporate insiders will affect innovation. To do this, we augment the baseline specification 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 traits after a country first enforces its insider trading laws.

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 two metrics 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 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 U.S. 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.

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 opacity because of the comparatively high costs of valuing innovative endeavors. However, in only 23% of industries are *High Tech* and *Intangibility* both equal to one.[7] 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 innovative industry. Similarly, two industries might have equal degrees of natural innovativeness, but one might be more opaque. In this case, enforcement would have a bigger impact on valuations in the more opaque industry and therefore have a

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

bigger impact innovation in the naturally more opaque industry. Thus, we examine both categories of industry traits, while recognizing that there is overlap.

3.3 Preliminary evidence regarding the validity of these strategies

In this subsection, we present four 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 shown in *Table 3*, pre-existing patent-based measures of innovation do not predict the timing of the first enforcement action.[8] We control for economic and financial development (*GDP*, *GDP per capita*, *Stock*/*GDP*, and *Credit*/*GDP*) and important characteristics related to a country's legal institution and political status. Specifically, we include legal origin, i.e., whether the country has common law or civil law heritage, because La Porta et al. (1998, 2008) and the subsequent literature emphasize how legal heritage can influence an assortment of laws concerning financial contracting. We also include a score measure of the extent of democracy in a country (*Polity*), which ranges from -10 (strongly autocratic) to +10 (strongly democratic), legislature fractionalization (i.e., the probability that two randomly-picked representatives in the legislature would come from two different parties), and indicators of political orientation of the largest party in the government (*Right*, *Left* and *Central*).[9] In all the five specifications, patent-based measures of innovation enter the regression insignificantly. 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:

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

$Innovation_{c,t}$ is either *Patent Count* ^{c} *Citation* ^{c}, which are our two, core patent-based indicators of innovation. $\text{Enforce}_{c,\tau}$ 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

[8] *Table 3* provides the results for the sample of countries in which the country did not enforce its insider trading laws before the start of the sample period. This includes both countries that enforced their laws during the sample period and those that did not enforce their insider trading laws during the sample period. The same results hold when only including countries that enforced their laws during the sample period.

[9] *Polity* is obtained from the Polity IV database; *Fractionalization* and political orientation (*Right*, *Left*, *Central*) are obtained from the Database of Political Institution (Beck et al., 2001).

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 $\text{Enforce}_{c,-10}$ while all the years beyond 15 years after the initial enforcement captured by the dummy $Enforce_{c,+15}$. The year of initial enforcement is dropped from the regression. To center the figure, we subtract the average value of the estimated values of $\alpha_{1,\tau}$ in the pre-enforcement period from each coefficient estimate. We then plot the estimated coefficients (minus this pre-enforcement mean). We also include the 95% confidence interval, which is adjusted for country level clustering. Thus, the confidence intervals evaluate whether each estimated parameter is significantly different from the pre-enforcement mean. 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. Thus, if the enforcement of insider trading laws is simply linked to innovation through its association with overall economic or financial development, this will be captured by the control variables.

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 enforcement 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. The second key finding confirms the results from the hazard model: There is not a 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 immediate and enduring simulative effect on the quantity (*Patent Counts*^{c}) and quality (Citation^c) of patenting.

Fourth, we employ a discontinuity approach to assess whether there are similar changes in other factors that might influence innovation when countries start enforcing their insider trading laws, which may confound the interpretation of the results presented below. For example, the work by Beny (2013) and others suggests that factors associated with international trade and overall financial development have shaped and been shaped by insider trading laws. Thus, we build on the dynamic specification in equation (3), and use *Credit/GDP* or *Trade/GDP* as dependent variable. *Credit/GDP* measures the development of domestic credit market; *Trade/GDP* gauges the intensity of international trade. As shown in *Figure 3*, nether the credit markets or the international trade changes in the same way that the patent-based indicators change after enforcement; indeed, neither *Credit/GDP* nor *Trade/GDP* changes appreciably around the date when countries start enforcing their insider trading laws. These findings reinforce the validity of our identification strategy.

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 baseline specification 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 approach, in which we access the heterogeneous response of industries to enforcement.

4.1 Baseline Specification

Table 4 presents the regression results from the baseline equation (1) 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 4* 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).

To address concerns that countries adopt packages of policy reforms at the same that they start enforcing insider trading laws, potentially confounding our identification strategy, we include an assortment of policy indicators in *Table 5*. Specifically, into the *Table 4* regressions we now include (1) *Credit Control*, which is an index of the restrictiveness of reserve requirements, existence of mandatory credit allocation requirements, and credit ceilings, with greater index for fewer restrictions, (2) *Interest Rate Control*, which measures the inverse of the extent to which the authorities control interest rates, (3) *Entry Barriers*, which measures the ease of foreign bank entry and the extent of competition in the domestic banking sector (e.g., restrictions on branching), (4) *Bank Supervision*, which measures the degree of supervision over the banking sector, (5) *Bank Privatization*, which measures the presence of state owned banks, (6) *Capital Control*, which measures restrictions on international capital flows, and again with greater value associated with fewer restrictions, (7) *Securities Market*, which measures the level of development of securities markets and restrictions on foreign equity ownership, (8) *Financial Reform Index*, which is the sum of the previous seven variables, (9) *Liberal Capital Markets*, which is defined as one after a country officially liberalized its capital market and zero otherwise (i.e. formal regulatory change after which foreign investors officially have the opportunity to invest in domestic equity securities), where the official liberalization date is obtained from Bekaert and Harvey (2000) and augmented by Bekaert et al. (2005) for 68 countries in our sample. *Table 1* provides detailed definitions of these variables.

The results are robust to controlling for these indicators of policy reforms. *Table 5* summarizes the results from 45 regressions, as we examine each of the nine policy reform indicators individually for each of the five patent-based indicators of innovation. The regressions continue to also control for country, industry, and year fixed effects along with the time-varying country and industry controls. As shown, even when controlling for these policy reforms, *Enforce* enters each of the regressions significantly. Indeed, when controlling for these policy indicators, the estimated coefficient varies little from the estimates reported in *Table 4*. These results help mitigate concerns that other policy changes that occur at the same time as the enforcement of insider trading laws account for the close association between enforcement and the uptick in innovation.

We provide three additional robustness tests in the Appendixes. First, we control for country-industry fixed effects and year fixed effects in assessing the relationship between innovation and enforcement. As shown in *Appendix B*, we find that *Enforce* enters positively and significantly in each of the patent-based regressions and the estimated point estimates on *Enforce* are very similar to those reported in *Table 4*. This robustness check ensures that the results are not confounded by any time-invariant characteristics specific to each industry in each country.

Second, we examine whether the results hold on both the extensive and intensive margins. Specifically, as explained in the Section 2, our baseline sample excludes country-industry observations in which we find no evidence of patenting activity. In this way, *Table 4* focuses on the intensive margin. In *Appendix C*, we include those observations in which we have no evidence of patenting and impose a value of zero for those country-industry observations. In this way, *Appendix C* includes the extensive margin. As shown, all of the results hold when using this large sample. Apparently, after a country starts enforcing its insider trading laws, existing innovative industries start innovating more and formally non-innovative industries start innovating.

Third, we conduct a placebo test by examining the date that a country enacts insider trading laws. As discussed, earlier work argues and finds that enforcement, not enactment, curtails insider trading. Thus, if the reduction in insider trading stimulates innovation, we should find that including the enactment date should neither affect the estimated impact of *Enforce* nor should the enactment date provide much additional explanatory power. This is what we find. As reported in *Appendix D*, the enactment of insider trading laws does not help account for changes in the patent-based indicators and including the enactment date does not alter the findings on *Enforce*.

4.2 Heterogeneous Responses by Industry

In this subsection, we evaluate cross-industry changes in innovative activity after a country starts enforcing its insider trading laws and assess whether these patterns are consistent with particular theoretical perspectives on how insider trading affects innovation. In particular, one class of models emphasizes that the enforcement of insider trading laws removes an impediment to the market more fully and accurately valuing innovative projects and thereby encourages more investment in innovative activities that have positive net present values (NPVs) when valued in a setting with no informational asymmetries between corporate insiders and outsiders. From this perspective,, 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

Based on equation (2), *Table 6* presents our assessment of whether naturally innovative industries experience larger increases in patent-based measures of innovation after a country starts enforcing its insider trading laws than other industries. In each panel, there are five regressions, where the dependent variable is one of the five patent-based measures. The explanatory variable of interest is the interaction terms, *High Tech*Enforce* in Panel A and *Innovation Propensity*Enforce* in Panel B, 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 in Panel A, 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. 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.

Panel B presents similarly strong 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* enters 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.

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, several models predict that enforcing insider trading laws will encourage 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 assess whether the enforcement of insider trading laws has a more pronounced and positive impact on innovation in both naturally innovative and opaque industries.

As reported in *Table 7*, we find that more opaque industries—as proxied by *Intangibility* = 1 in Panel A—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 26% 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 Panel B, the results confirm the finding that enforcement has a disproportionately large, positive effect on innovation in more opaque industries. 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*. These findings are consistent with theories emphasizing that the enforcement of insider trading laws reduces the disincentives to expending resources on valuing projects and the reduction of these disincentives will have an especially big impact on naturally innovative and opaque industries.[10]

We were concerned that the results might be driven by a particular group of countries. For instance, perhaps the results are driven by either highly developed economies or highly underdeveloped economies, in which a few additional patents after enforcement might have a big impact on the estimated coefficients. We were also concerned the results could be driven only by countries with highly developed or underdeveloped stock markets or only by countries with market-oriented political ideologies. Thus, we conduct the analyses while splitting the sample into several subgroup, including by the economic size of the economy (median *GDP*), the level of economic development (median *GDP per capita*), the level of stock market development (median *Stock/GDP*), and political orientation (, i.e., whether the political orientation is more *Right* or more *Center/Left*). As shown in *Appendix E*, all of the different patent-based measures of innovation rise appreciably in naturally innovative industries after a country starts enforcing its insider trading laws across *all* of the subsamples

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, several theories emphasize that effective constraints on insider trading will enhance the valuation of innovative activities and thereby facilitate 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 acquisitions by other entities are two major exit

[10] In unreported robustness tests, we examine the sensitivity of the *Table 6* and *Table 7* results to including additional controls. In particular, we interact *High Tech*, *Innovation Propensity*, *Intangibility*, and *STD of MTB* with the policy indicators used in *Table 5* and add those interaction terms to the regressions in *Table 6* and *Table 7*. We confirm that all of the results in *Table 6* and *Table 7* when adding these interaction terms. Consistent with the view that enforcing insider trading laws improves valuations and these improvements have a particularly large effect on naturally innovative and opaque industries, we find that *High Tech*Enforce*, *Innovation Propensity*Enforce*, *Intangibility*Enforce*, and *STD of MTB*Enforce* continue to enter the innovation regressions positively and significantly with similar point estimates as to those reported in *Table 6* and *Table 7*.

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 starts enforcing its 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 8* 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 8*, 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 of issuances.

The estimated magnitudes are large. For example, the *Table 8* 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 8* 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 provide evidence consistent with the view that legal systems that protect outside investors from corporate insiders accelerate technological innovation. Based on over 75,000 industry-country-year observations across 94 economies from 1976 to 2006, we discover that patent intensity, scope, impact, generality, and originally of patenting activity all rise markedly after a country first starts enforcing its insider trading laws. Moreover, we find that the pattern of cross-industry changes in innovative activity is consistent with theories emphasizing that when insiders can trade on non-public information this dissuades other investors from expending the resources necessary for accurately valuing innovative activities, which impedes the efficient allocation of capital to innovative endeavors. In particular, several theories stress that 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.

Moreover, our findings on equity issuances emphasizes that restricting insider trading boosts equity issuances, especially among firms in naturally innovative industries. To the extent that insider trading impedes the ability of markets to accurately value innovative activities and the resulting informational asymmetry impedes the ability of such firms to issue equity, we should find that restricting insider trading facilitates equity issuances by such firms. This is what we find. We discover that industries that are naturally more innovative experience a much bigger increase in IPOs and SEOs after a country starts enforcing its insider trading laws than other types of industries.

The results in this paper contribute to a large and emerging body of evidence suggesting that laws, regulations, and enforcement mechanisms that foster transparency, integrity, and broad participation enhance the functioning of financial systems with positive ramifications on economic activity, as discussed in Barth et al. (2006), La Porta et al. (2008), and Beck et al. (2010). We find that legal systems that impede insider trading and thereby encourage investors to acquire information and value firms more accurately exert a material impact on innovation. Since innovation is vital for sustaining improvements in living standards, these results highlight the centrality of financial market policies for promoting economic prosperity.

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Table 1 Variable Definition

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): $W_L^K, L = 0, \ldots, 28$; $W_L^K = 1/\overline{S}_L^K$, where $\overline{S}_L^K$ 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 $\overline{S}_L^K$ 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 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	PATSTAT Database

	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 Characteristics	
Bank Privatization	A financial liberalization measure based on the presence of state ownership in the banking sector; it is constructed as an additive score variable, with 0 indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	IMF
Bank Supervision	A financial liberalization measure based on the degree of banking sector supervision, including capital adequacy ratio and independence of supervisory body; it is constructed as an additive score variable, with 0 indicating not regulated, 1 indicating less regulated, 2 indicating largely regulated and 3 indicating highly regulated.	IMF
Capital Control	A financial liberalization measure based on restrictions over international capital flows and existence of unified exchange rate system; it is constructed as an additive score variable, with 0	IMF

	indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	
Central	The political orientation of the largest party in the government is central, i.e., centrist.	Database of Political Institution (Beck et al., 2001)
Common Law	An indicator variable equal to one if the legal origin of a country belongs to common law system.	La Porta et al. (2008)
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 companies.	World Bank-WDI
Credit Control	A financial liberalization measure based on the strictness of credit control, including reserve requirements, existence of mandatory credit allocation and credit ceilings; it is normalized between 0 and 3, with 0 indicating the least liberalized while 3 the fully liberalized.	IMF
Fractionalization	The probability that two deputies picked at random from the legislature will be of different parties.	Database of Political Institution
Financial Reform Index	An aggregated financial liberalization measure, equal to the summation of Credit Control, Interest Rate Control, Entry Barriers, Bank Supervision, Bank Privatization, Capital Control and Securities Market, ranging from 0 to 27.	IMF
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 real GDP per capita measured in current U.S. dollar.	World Bank-WDI
Entry Barriers	A financial liberalization measure based on the ease of foreign bank entry and the extent of competition in the domestic banking sector (e.g., restrictions on banking); it is constructed as an additive score variable, with 0 indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	IMF
Liberal Capital Markets	A financial liberalization measure based on the official liberalization date, after which foreign investors officially have the opportunity to invest in domestic equity securities; it is set to one for years after the official date and zero otherwise.	Bekaert and Harvey (2000) Bekaert et al. (2005)
Interest Rate Control	A financial liberalization measure based on the extent interest rate liberalization, including that of deposit rates and lending rates; it is constructed as an additive score variable, with 0 indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	IMF
Left	The political orientation of the largest party in the government is left, i.e., left-wing, socialist, communist or social democrat.	Database of Political Institution
Polity	A composite index indicating the level of democracy and autocracy, ranging from -10 (strongly autocratic) to +10 (strongly democratic).	Polity IV Database
Right	The political orientation of the largest party in the government is right, i.e., right-wing, conservative or Christian democratic.	Database of Political Institution
Securities Market	A financial liberalization measure based on the measures to develop securities market and restrictions on the foreign equity ownership; it is constructed as an additive score variable, with 0 indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	
Stock/GDP	The value of listed shares to GDP.	World Bank

		-FDS
Trade/GDP	Import and export of goods and services as fraction of GDP.	World Bank-WDI
	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
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
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 Platinum
IPO Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) raised via IPO in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC Platinum
Proceeds per IPO	The natural logarithm of one plus the average amount of dollar proceeds per IPO (mil$) 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 Platinum
Proceeds per Issue	The natural logarithm of one plus the average amount of dollar	SDC Platinum

	proceeds per equity issuance (mil$) made in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	
Proceeds per SEO	The natural logarithm of one plus the average amount of dollar proceeds per SEO (mil$) 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 Platinum
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 Platinum
SEO Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) raised via SEO in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC Platinum
Total Issue Number	The natural logarithm of one plus the total number of equity issuance in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC Platinum
Total Proceeds	The natural logarithm of one plus the total amount of dollar proceeds (mil$) 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 Platinum

Table 2 Summary Statistics

This table presents the unweighted summary statistics across all the 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 economic characteristics include *GDP*, *GDP per capita* (both in natural logarithm), equity/credit market development (*Stock/GDP*, *Credit/GDP*), international trade (*Trade/GDP*), and a series of measures of financial liberalization policies; country-level legal and political factors include legal origin (*Common Law*), the extent of democracy (*Polity*), legislature fractionalization (*Fractionalization*), and political orientation of the largest party in the government (*Right*, *Central*, *Left*). Industry-level variables include the share of industry's export over total export to the U.S. (*Export to US*) and a series of U.S.-based industry indicators representing different natural rate of innovation (*High Tech* and *Innovation Propensity*) 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. Except for country-level variables, whose summary statistics are calculated over country-year observations, the summary statistics of all other variables are calculated over all the industry-country-year observations. Table 1 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
Country-level Economic Factors						
Credit/GDP	1,990	0.2543	0.7326	0.6200	1.3407	0.4761
GDP	2,090	22.4281	24.7829	24.8652	27.0515	1.7400
GDP per capita	2,087	6.7009	8.4857	8.5180	10.1760	1.3165
Stock/GDP	2,090	0	0.2990	0.0911	0.8723	0.4965
Trade/GDP	2,032	0.3235	0.7952	0.6448	1.3970	0.5676
Credit Control	1,643	0	1.8608	2	3	1.0970
Interest Rate Control	1,643	0	2.2149	3	3	1.1678
Entry Barriers	1,643	0	1.9848	2	3	1.1311
Bank Supervision	1,643	0	1.0456	1	3	1.0422
Bank Privatization	1,643	0	1.4820	1	3	1.1727
Capital Control	1,643	0	2.0030	2	3	1.0900
Securities Market	1,643	0	1.9598	2	3	1.0445
Financial Reform Index	1,643	3	12.5510	14	20	6.0853
Liberal Capital Markets	1,662	0	0.6360	1	1	0.4813

Country-level Legal and Political Factors						
Common Law	2,163	0	0.2723	0	1	0.4453
Polity	1,943	-7	5.1374	9	10	6.6076
Fractionalization	1,913	0.0473	0.5843	0.6576	0.8250	0.2504
Right	1,948	0	0.3701	0	1	0.4830
Central	1,948	0	0.1165	0	1	0.3209
Left	1,948	0	0.3424	0	1	0.4746
Industry-level characteristics						
Export to US	76,321	0	0.0207	0	0.0534	0.0706
High Tech	73,410	0	0.4831	0	1	0.4997
Innovation Propensity	73,219	0	0.4848	0	1	0.4998
Intangibility	76,321	0	0.4925	0	1	0.4999
STD of MTB	75,059	0	0.4817	0	1	0.4997
Industry-level 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 3 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. Counties that enforced the insider trading laws before 1976 are excluded from the duration model analysis. Among the remaining countries, we treat those without law enforcement within our sample period as always "at risk" of enforcing the law; for those with law enforcement within our sample period, they drop out of the sample once the law was enforced. Control variables are grouped into economic, legal and political factors. Measurements of economic development include *GDP*, *GDP per capita*, *Stock*/*GDP* and *Credit*/*GDP*. Measurements of legal and political environment include 1) an indicator variable for legal origins (*Common Law*) that equals one if a country has common law origin; 2) the composite index of democracy and autocracy (*Polity*), ranging from -10 (strongly autocratic) to +10 (strongly democratic); it is obtained from the Polity IV Database; 3) legislature fractionalization (*Fractionalization*), defined as the probability that two deputies picked at random from the legislature will be of different parties; it is obtained from the Database of Political Institution (Beck et al., 2001); 4) three indicator variables representing political orientation of the largest party in the government: right-wing / conservative / Christian democratic (*Right*), centrist (*Central*) and left-wing / socialist / communist / social democrat (*Left*), where *Left* serves as the base group; they are obtained from the Database of Political Institution. 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.

Dependent variable	ln(survival time)				
	(1)	(2)	(3)	(4)	(5)
Patent Count^{c}	-0.1927				
	(-1.37)				
Patent Entities^{c}		-0.1916			
		(-1.16)			
Citation^{c}			-0.0643		
			(-0.55)		
Generality^{c}				-0.0182	
				(-0.10)	
Originality^{c}					0.0711
					(0.33)
Observations	1,268	1,268	1,268	1,202	1,231
Controls	Yes	Yes	Yes	Yes	Yes

Table 4 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 innovative 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*. Table 1 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)
Panel A.					
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.					
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 5 Insider Trading Law Enforcement and Innovation: Controlling for Policy Changes

This table presents the effect of the enforcement of insider trading laws on innovation, controlling for other policy changes and reforms for financial liberalization (FL). We follow the following specification: $\text{Innovation}_{i,c,t} = \beta_0 + \beta_1 \text{Enforce}_{c,t} + \beta_2 \text{FL}_{c,t} + \lambda X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$. We use an assortment of FL measures from columns 1) to 9): 1) *Credit Control* evaluates the restrictiveness of reserve requirements, existence of mandatory credit allocation and credit ceilings, ranging from 0 (i.e., fully repressed) to 3 (fully liberalized); 2) *Interest Rate Control* measures the extent of interest rate liberalization, with 0, 1, 2, 3 indicates fully repressed, partially repressed, largely liberalized and fully liberalized, respectively; 3) *Entry Barriers* captures the ease of foreign bank entry and the extent of competition in the domestic banking sector (e.g., restrictions on branching), which also ranges from 0 to 3, indicating the least liberalized to the fully liberalized; 4) *Bank Supervision* measures the degree of supervision over the banking sector, ranging from 0 (not regulated) to 3 (highly regulated); 5) *Bank Privatization* proxies the presence of state ownership, ranging from 0 to 3, where 0 means the highest level of state ownership (i.e., full repressed), while 3 means the lowest (i.e., fully liberalized); 6) *Capital Control* evaluates the restrictions on international capital flow, ranging from 0 (i.e., fully repressed) to 3 (fully liberalized); 7) *Securities Market* evaluates measures to develop securities market and restrictions on the foreign equity ownership, ranging from 0 (i.e., fully depressed) to 3 (i.e., fully liberalized); 8) *Financial Reform Index* is the sum of the previous seven variables; Variables in columns 1)-8) are obtained from IMF, available for a maximum of 71 countries in our sample ; 9) *Liberal Capital Markets* is defined as one after a country officially liberalized its capital market and zero otherwise (i.e. formal regulatory change after which foreign investors officially have the opportunity to invest in domestic equity securities), where the official liberalization date is obtained from Bekaert and Harvey (2000) and augmented with Bekaert et al. (2005) for 68 countries in our sample. Control variables include *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. Table 1 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.

Financial Liberalization (FL)	Credit Control (1)	Interest Rate Control (2)	Entry Barriers (3)	Bank Supervision (4)	Bank Privatization (5)	Capital Control (6)	Securities Market (7)	Financial Reform Index (8)	Liberal Capital Markets (9)
Panel A. Patent Counts									
Enforce	0.2514**	0.2552**	0.2406**	0.2524**	0.2245**	0.2496**	0.2593**	0.2389**	0.3261***
	(2.10)	(2.12)	(2.14)	(2.21)	(2.09)	(2.09)	(2.21)	(2.12)	(2.78)
Panel B. Patent Entities									
Enforce	0.2018**	0.2046**	0.1921**	0.2038**	0.1776*	0.2007**	0.2056**	0.1907**	0.2765***
	(1.99)	(2.01)	(2.02)	(2.07)	(1.96)	(1.96)	(2.09)	(1.98)	(2.82)
Panel C. Citations									
Enforce	0.3678***	0.3717***	0.3543***	0.3774***	0.3406***	0.3745***	0.3660***	0.3599***	0.4308***
	(2.79)	(2.78)	(2.88)	(2.92)	(2.87)	(2.77)	(2.92)	(2.83)	(3.06)
Panel D. Generality									
Enforce	0.1471***	0.1496***	0.1456***	0.1474***	0.1302***	0.1483***	0.1456***	0.1427***	0.1831***
	(2.76)	(2.75)	(2.80)	(2.96)	(2.95)	(2.69)	(3.02)	(2.80)	(3.22)
Panel E. Originality									
Enforce	0.1489**	0.1497**	0.1468**	0.1482***	0.1332**	0.1497**	0.1533***	0.1428**	0.1960***
	(2.53)	(2.52)	(2.53)	(2.65)	(2.49)	(2.48)	(2.81)	(2.52)	(3.07)
FL	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6 Insider Trading Law Enforcement and Innovation: By Natural Rate of Innovation

This table shows the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different natural rate of innovation. We use the following specifications: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{High Tech}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ (Panel A) and $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{Innovation Propensity}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ (Panel B). *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. *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 variable is *Export to US* and other characteristics are subsumed by the country-year dummies $\delta_{\text{c,t}}$ and industry-year dummies $\delta_{i,\text{t}}$. Table 1 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)
Panel A.					
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
Panel B.					
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 7 Insider Trading Law Enforcement on Innovation: By Information Asymmetry

This table demonstrates the differential effects of the enforcement of insider trading laws on the innovative activities across industries that are characterized with different extent of information asymmetry. The specification follows: $\text{Innovation}_{i,c,t} = \beta_0 + \beta_1\text{Enforce}_{c,t} \times \text{Intangibility}_i + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}$ (Panel A) and $\text{Innovation}_{i,c,t} = \beta_0 + \beta_1\text{Enforce}_{c,t} \times \text{STD of MTB}_i + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}$ (Panel B). *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. *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 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 variable is *Export to US* and other characteristics are subsumed by the country-year dummies $\delta_{c,t}$ and industry-year dummies $\delta_{i,t}$. Table 1 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)
Panel A.					
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
Panel B.					
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 8 Insider Trading Law Enforcement and Equity Issuance

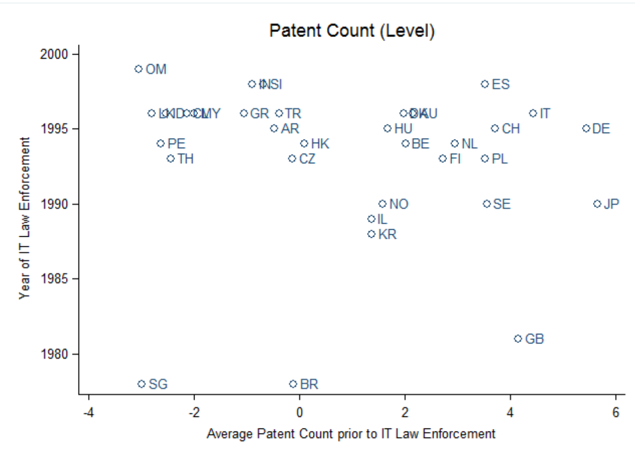
This table lays out the effect of the enforcement of insider trading laws on equity issuance activities at industry-country level, where industries are differentiated by the natural extent of innovation. We examine total equity issuances and specific types of equity issuances, namely, initial public 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.

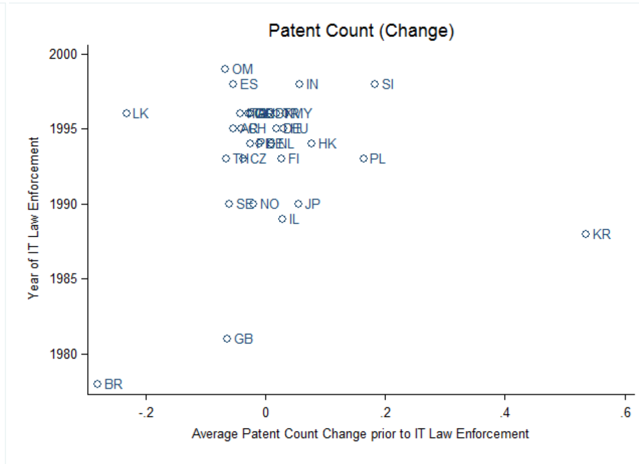
Dependent variables	IPO Number	IPO Proceeds	Proceeds per IPO	SEO Number	SEO Proceeds	Proceeds per SEO	Total Issue Number	Total Proceeds	Proceeds per Issue
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A.									
High Tech × Enforce	0.1022***	0.2650***	0.1884***	0.1305***	0.3237***	0.2191***	0.1690***	0.3969***	0.2542***
	(4.24)	(4.29)	(4.42)	(4.78)	(4.95)	(4.60)	(5.00)	(5.18)	(4.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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.									
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

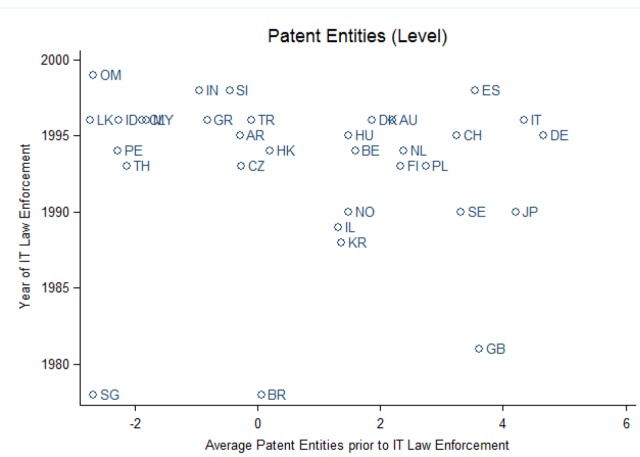
The set of figures plot the average level of innovation and the average rate of change in innovation before the initial enforcement of the insider trading laws against the year of the initial enforcement. Innovation takes one of the five patent-based measures of innovation at country level: *Patent Count*^{c}, *Patent Entities*^{c}, *Citation*^{c}, *Generality*^{c} and *Originality*^{c} respectively. Table 1 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.

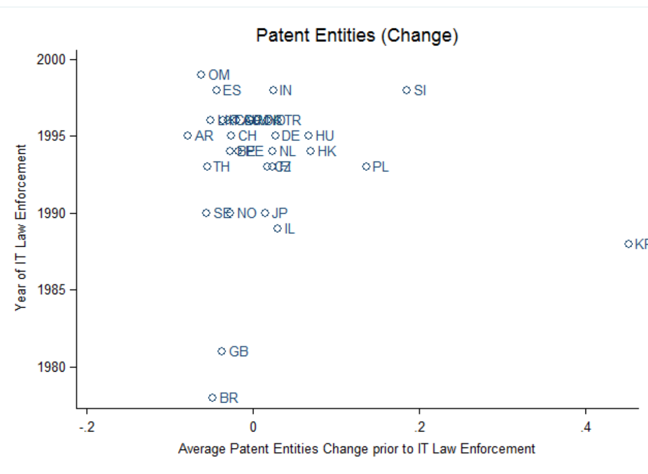
(1) Patent Count



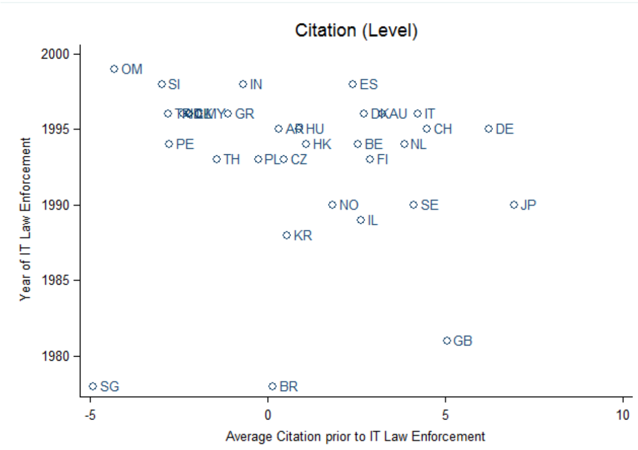


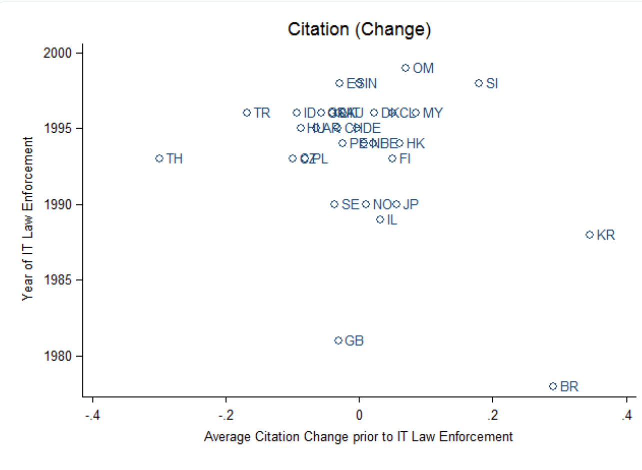
(2) Patent Entities



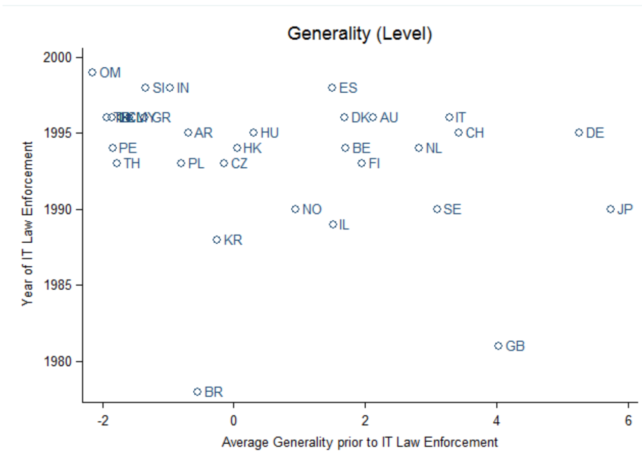


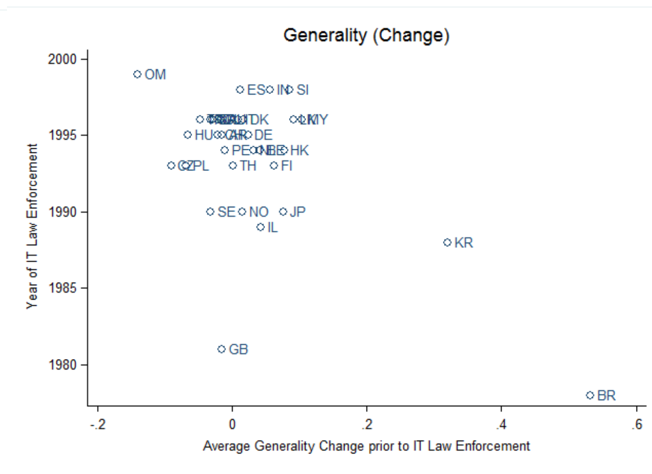
(3) Citation



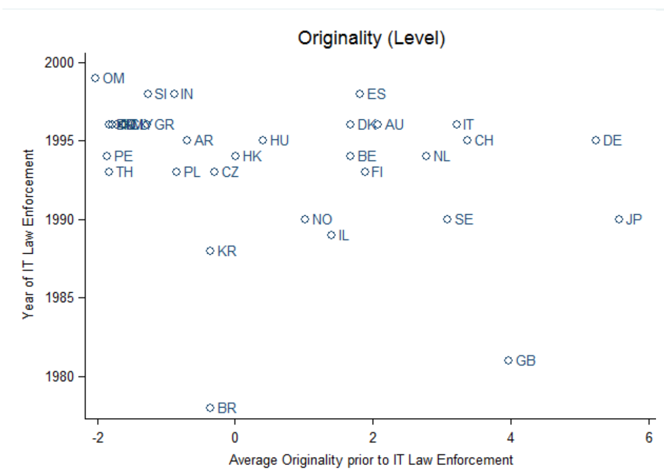


(4) Generality





(5) Originality



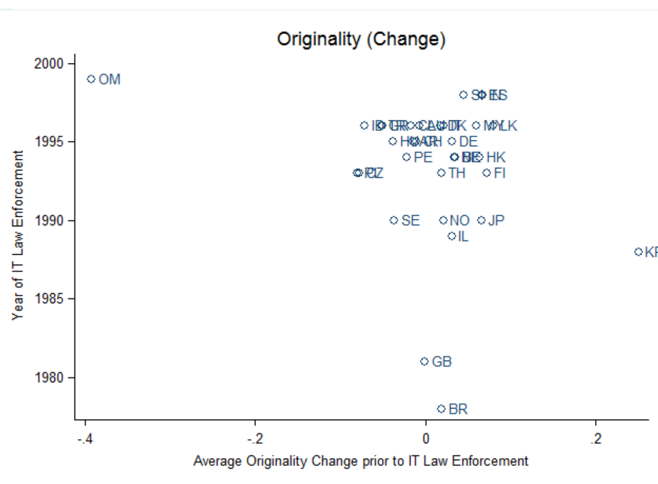
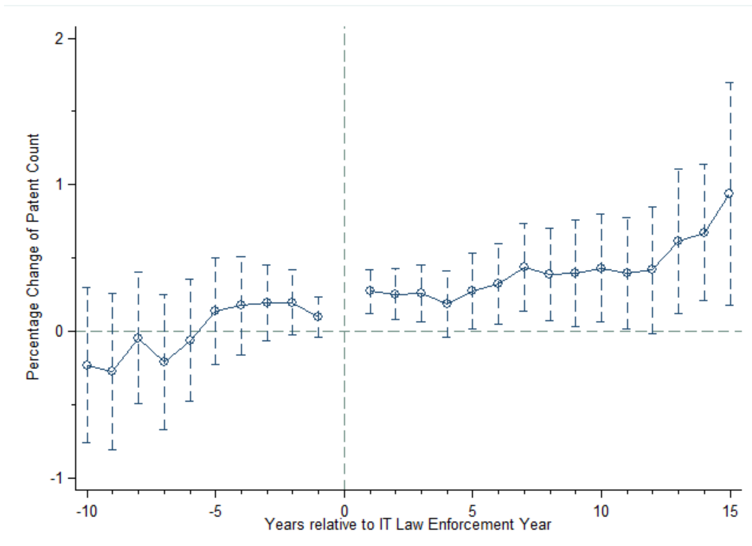


Figure 2 Dynamics of Insider Trading Law Enforcement and Innovation

The figures plot the dynamic impact of the enforcement of insider trading laws on country-level 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 patent-based measures of innovation at country level: *Patent Count* ^{c} and *Citation* ^{c}. Control variables include *GDP*, *GDP per capita*, *Stock*/*GDP*, and *Credit*/*GDP*. Table 1 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.

(1) Patent Count



(2) Citation

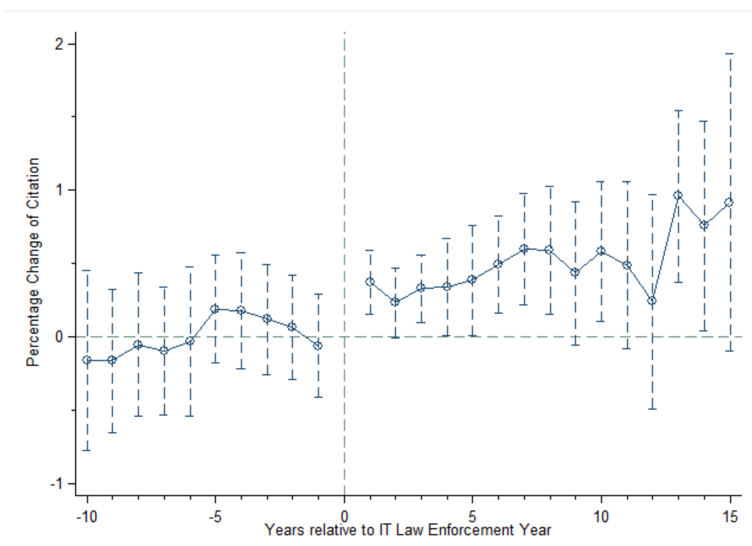
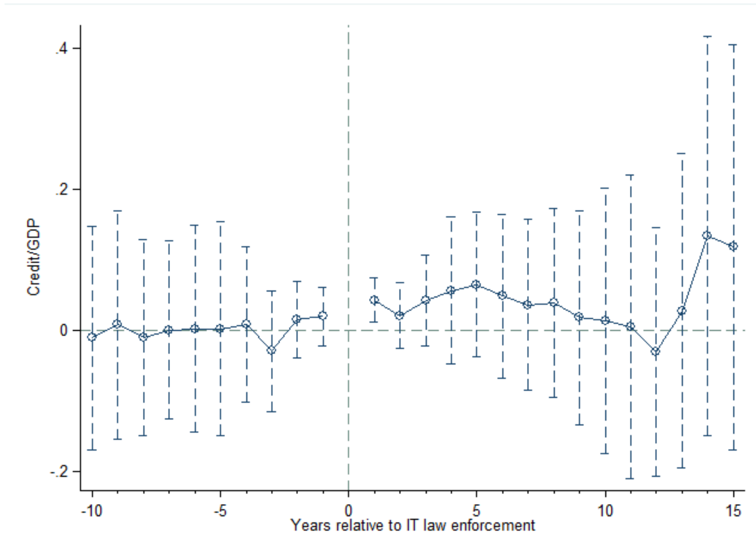


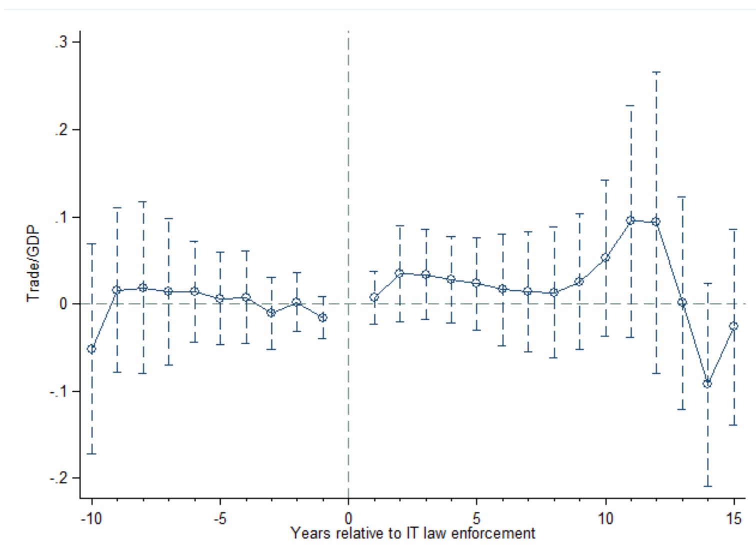
Figure 3 Other Market Conditions around Insider Trading Law Enforcement

The figures plot the dynamics of credit market development and trade activities around insider trading law enforcement. We use the following specification: $\text{Covariates}_{c,t} = \alpha_0 + \alpha_{1,\tau} \sum_{\tau=t-10}^{\tau=t+15} \text{Enforce}_{c,\tau} + \delta_c + \delta_t + \varepsilon_{c,t}$, where *Covariate* takes the value of *Credit*/*GDP* and *Trade*/*GDP* respectively. 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.

(1) Credit/GDP



(2) Trade/GDP



Appendix A 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. Table 1 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

**Appendix B Insider Trading Law Enforcement and Innovation:
Robustness with Country-industry and Year Fixed Effects**

In this table, we present the robustness test results of baseline analysis using country-industry and year fixed effects. We use the following specification: $\text{Innovation}_{i,c,t} = \alpha_0 + \alpha_1\text{Enforce}_{c,t} + \gamma X'_{i,c,t} + \delta_{c,i} + \delta_t + \varepsilon_{i,c,t}$. *Enforce* 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*. Table 1 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)
Enforce	0.2599**	0.2065**	0.3619**	0.1596***	0.1820***
	(2.11)	(1.99)	(2.57)	(2.63)	(2.72)
Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Country-Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	70,319	70,319	70,319	65,641	67,014
Adjusted R-squared	0.941	0.947	0.910	0.942	0.933

Appendix C Insider Trading Law Enforcement and Innovation: Robustness at Extensive Margin

This table presents robustness test results of the baseline analysis based on the sample with both intensive and extensive margin, where we include industry-country-years when no patents are filed and assign a value of zero to them. We use 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 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*. Table 1 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)
Enforce	0.2205**	0.1746*	0.3791***	0.1323**	0.1847***
	(2.07)	(1.91)	(2.60)	(2.50)	(3.05)
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	118,816	118,816	118,816	114,138	115,511
Adjusted R-squared	0.829	0.839	0.845	0.741	0.745

Appendix D Insider Trading Law Enactment and Innovation: Robustness

In this table we present the robustness tests of the baseline analysis including the enactment events of insider trading laws. We follow the following specification: $\text{Innovation}_{i,c,t} = \alpha_0 + \alpha_1 \text{Enact}_{c,t} + \gamma X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$ and $\text{Innovation}_{i,c,t} = \alpha_0 + \alpha_1 \text{Enact}_{c,t} + \alpha_2 \text{Enforce}_{c,t} + \gamma X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$. *Enact* is equal to one for years after the law is enacted in a country; *Enforce* 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*. Table 1 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	Patent Count	Patent Entities	Citation	Generality	Originality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Enact	-0.1295	-0.0864	-0.2248	-0.1078	-0.1279*	-0.1365	-0.0919	-0.2346*	-0.1147	-0.1345*
	(-0.98)	(-0.78)	(-1.53)	(-1.27)	(-1.68)	(-1.05)	(-0.84)	(-1.65)	(-1.39)	(-1.80)
Enforce						0.2633**	0.2087**	0.3733***	0.1635***	0.1860***
						(2.22)	(2.05)	(2.74)	(2.82)	(3.01)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	70,319	70,319	70,319	65,641	67,014	70,319	70,319	70,319	65,641	67,014
Adj. R-squared	0.857	0.872	0.862	0.781	0.787	0.859	0.873	0.863	0.782	0.789

Appendix E Insider Trading Law Enforcement and Innovation: Sub-sample Analysis

This table presents the sub-sample results of insider trading law enforcement and innovation. We first calculate the median value of *GDP*, *GDP per capita*, and *Stock/GDP* for each country within the sample period and then split sample into two groups based on the median, or by the political orientation of the largest party. We follow the specification: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Enforce}_{\text{c,t}} \times \text{High Tech}_i + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ in each sub-sample. Control variable is *Export to US* and other characteristics are subsumed by the country-year dummies $\delta_{\text{c,t}}$ and industry-year dummies $\delta_{i,\text{t}}$. Table 1 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)
Panel A. Subsample by GDP					
High GDP					
High Tech×Enforce	0.2781***	0.2084**	0.2145**	0.3800***	0.3502***
	(2.69)	(2.51)	(2.57)	(3.46)	(3.26)
Low GDP					
High Tech×Enforce	0.3736***	0.3501***	0.5040***	0.2430***	0.2617***
	(4.11)	(4.41)	(3.67)	(2.69)	(2.99)
Panel B. Subsample by GDP per capita					
High GDP per capita					
High Tech×Enforce	0.3621***	0.3191***	0.3034***	0.4576***	0.4384***
	(4.39)	(4.57)	(4.35)	(5.19)	(4.84)
Low GDP per capita					
High Tech×Enforce	0.2953**	0.2390***	0.3256***	0.1566	0.1729
	(2.16)	(2.56)	(2.63)	(1.239)	(1.43)
Panel C. Subsample by Stock/GDP					
High Stock/GDP					
High Tech×Enforce	0.4508***	0.3844***	0.3746***	0.5130***	0.5012***
	(5.83)	(6.18)	(5.78)	(6.30)	(6.22)
Low Stock/GDP					
High Tech×Enforce	0.2556**	0.2352**	0.3274**	0.1343	0.1495
	(2.45)	(2.57)	(2.43)	(1.39)	(1.57)
Panel D. Subsample by Political Orientation					
Right					
High Tech×Enforce	0.4715***	0.4088***	0.4625***	0.4542***	0.4487***
	(5.18)	(5.61)	(5.10)	(5.12)	(5.14)
Central and Left					
High Tech×Enforce	0.3970***	0.3345***	0.3573***	0.4299***	0.4250***
	(5.69)	(5.63)	(3.78)	(4.65)	(4.89)
Controls	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes