Insider Trading and Innovation

ROSS LEVINE, CHEN LIN, AND LAI WEI*

ABSTRACT

We assess whether restrictions on insider trading accelerate or slow technological innovation. Based on over 80,000 industry-country-year observations across 74 economies from 1976 to 2006, we find that enforcing insider-trading laws spurs innovation—as measured by patent intensity, scope, impact, generality, and originality. Furthermore, the evidence is consistent with the view that restricting insider trading accelerates innovation by improving the valuation of, and increasing the flow of equity financing to, innovative activities.

August 2017

Key Words: Insider Trading; Financial Regulation; Patents; Finance and Economic Growth

JEL Classifications: G14; G18; O30; F63

* Levine: University of California, Berkeley, rosslevine@berkeley.edu. Lin: University of Hong Kong, chenlin1@hku.hk. Wei: Lingnan University, laiwei2@ln.edu.hk. For helpful comments and suggestions, we are grateful to Sumit Agarwal, Utpal Bhattacharya, Gustavo Manso, Huasheng Gao, Harald Hau, Po-Hsuan Hsu, Kai Li, Lee Fleming, Stephen Haber, Wes Hartmann, Jay Ritter, Yona Rubinstein, Farzad Saidi, Krishnamurthy Subramanian, Xuan Tian, Xu Yan, Bohui Zhang, and seminar participants at the Entrepreneurial Finance and Innovation around the World Conference in Beijing, the International Conference on Innovations and Global Economy held by Alibaba Group Research Centre, Zhejiang University, Geneva Graduate Institute of International and Development Studies, the American Financial Association meetings, the Hoover Institution's Working Group on Innovation, Intellectual Property, and Prosperity conference at Stanford University, the Edinburgh Conference on Legal Institutions and Finance, the University of California, Berkeley, and the University of Florida. We thank the Clausen Center for International Business and Policy for financial support.

1. Introduction

An enormous body of research examines how legal and financial systems shape economic growth. The finance and growth literature emphasizes that better functioning financial systems spur economic growth primarily by boosting productivity growth and technological innovation (e.g., King and Levine 1993, Levine and Zervos 1998, and Brown et al. 2009, 2012, 2016).[1] In turn, the law and finance literature finds that legal systems that protect minority shareholders from large shareholders foster better functioning financial systems (e.g., La Porta et al. 1997, 1998 and Brown et al. 2017).

What has received less attention, however, is whether legal systems that protect outside investors from corporate insiders influence the invention of new technologies, which is a major, if not the major, source of long-run growth. Research shows that stronger investor protection laws, more stringent corporate transparency regulations, and restrictions on insider trading boost R&D expenditures (Brown et al. 2013 and Brown and Martinsson 2017). However, while R&D expenditures directly measure corporate investments in research and development, they do not measure the quantity, impact, and quality of inventions.

In this paper, we first examine whether legal systems that restrict insider trading—trading by corporate officials or major shareholders on material non-public information—influence the invention of new technologies, as measured by patent intensity, scope, impact, generality, and originality. In this way, we evaluate whether one particular investor protection law, restrictions on insider trading, influences innovation. We then explore whether restricting insider trading influences patenting by shaping the valuation and financing of innovative activities in a theoretically predictable manner.

Our research contributes to an enduring debate about the impact of restricting insider trading on the valuation of firms and the efficiency of investment. For example, Fishman and Hagerty (1992) and DeMarzo et al. (1998) stress that insider trading allows corporate insiders to exploit other investors, which discourages those outside investors from expending resources to assess and value firms (e.g., Bushman et al. 2005, Fernandes and Ferreira 2009).[2] The resultant reduction in stock price informativeness can impair investment in difficult to assess activities such as innovation (e.g., Holmstrom 1989) and impede the use of stock prices to improve managerial incentives (e.g., Manso

[1] For more on the linkages between financial development and innovation, see Beck et al. (2000), Benfratello et al. (2008), Ayyagari et al. (2011), Amore et al. (2013), Fang et al. (2014), Hsu et al. (2014), Laeven et al. (2015), and Nanda and Rhodes-Kropf (2016).

[2] Leland (1992) notes that insider trading reveals information in public markets.

2011).[3] In contrast, Demsetz (1986) argues that insider trading can be a cost-efficient way to compensate large owners for undertaking the costly process of monitoring and governing corporations. Since it is especially difficult to exert sound governance over opaque activities, such as technological innovation, insider trading can be disproportionately important for fostering technological innovation. Thus, existing research suggests that restricting insider trading can either accelerate or slow innovation.

To assess whether restrictions on insider trading are associated with an overall increase or decrease in the rate of innovation, we use data on (1) the staggered enactment and enforcement of insider trading laws across countries and (2) six measures of patenting activity and impact. We obtain information on both the year when a country first enacts insider trading laws and the year when it first prosecutes a violator of those laws from Bhattacharya and Daouk (2002). We examine both enactment and enforcement because Bhattacharya and Daouk (2002) and other stress that only the actual enforcement of laws shapes the operation of financial markets. To measure innovation, we construct six patent-based indicators. We obtain information on patenting activities at the industry level in the 74 countries that enacted insider trading laws between 1976 through 2006 from the EPO Worldwide Patent Statistical Database (PATSTAT). We conduct our analyses at the industry level, and not at the firm level, because cross-country databases, such as Orbis, have very poor coverage of firms during our sample period. We compile a sample of 83,200 industry-country-year observations and calculate the following proxies for technological innovation: (1) the number of patents to gauge the intensity of patenting activity, (2) the number of forward citations to patents filed in this industry-country-year to measure the impact of innovative activity, (3) the number of patents in an industry-country-year that become “top-ten” patents, i.e., patents that fall into the top 10% of citation distribution of all the patents in the same technology class in a year, to measure high-impact inventions (Balsmeier et al. 2017), (4) the number of patenting entities to assess the scope of innovative activities (Acharya and Subramanian 2009), (5) the degree to which technology classes other than the one of the patent cite the patent to measure the generality of the invention, and (6) the degree to which the patent cites innovations in other technology classes to measure the originality of the invention (Hall et al. 2001).

We begin with preliminary analyses that simply differentiate by country and year and then

[3] Furthermore, from a textbook corporate governance perspective, if corporate decision makers focus on manipulating stock prices to maximize their private revenues from insider trading, then they will be correspondingly less focused on maximizing long-run shareholder value.

shift to our core analyses that examine whether the relationship between restricting insider trading and both innovation and new equity issuances vary across industries in a theoretically predictable manner. In our preliminary analyses, we regress the patent-based proxies of innovation, which are measured at the industry-country-year level, on (1) the enforcement indicator, which equals one after a country first enforces its insider trading laws and zero otherwise, and (2) the enactment indicator, which equals one after a country enacts restrictions on insider trading. The regressions also include country, industry, and year fixed effects and an assortment of time-varying country and industry characteristics. Specifically, we control for Gross Domestic Product (GDP) and GDP per capita since we were concerned that the size of the economy and the level of economic development might shape both innovation and policies toward insider trading. Since stock market and credit conditions could influence innovation and insider trading restrictions, we also include stock market capitalization as a share of GDP and credit as a share of GDP. Finally, factors shaping an industry's exports could also be correlated with innovation and insider trading restrictions, so we control for industry exports to the U.S.

We find that the enforcement of insider trading laws is associated with a statistically significant, economically large, and highly robust increase in each of the six patent-based measures of innovation. For example, the number of patents rises, on average, by 15% after a country first enforces its insider trading laws and citation counts rise by 29%. These results—both in terms of statistical significance and the estimated economic magnitudes—are robust to including or excluding time-varying country and industry controls.[4] On the other hand, we find no evidence that the enactment of insider trading laws shapes innovation; rather, it is only the enforcement of those laws that is tightly linked with innovation.

We were concerned that omitted variables might drive both technological innovation and insider trading restrictions, so we conducted several checks. Using a control function approach, we include many additional time-varying country-specific policy changes, including: (a) several indictors of securities market reforms and policies toward international capital flows, (b) an array of indicators of bank regulatory and supervisory policies, and (c) enactment of patent laws, measures of intellectual property rights protection, property rights protection more generally, and the effectiveness of the legal

[4] Furthermore, there might be concerns about using industry-level observations in these country-year analyses even when including industry fixed effects. Thus, as shown below, we aggregate the data to the country-year level and conduct the analyses at the country-level. All of the results hold.

system. Controlling for these factors does not alter the results.

We also show that there are 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. Neither the level nor the growth rate of the patent-based innovation measures predicts the timing of the enforcement of insider trading laws.[5] Furthermore, we use a discontinuity approach to assess whether the enforcement of insider trading restrictions is associated with a jump in other country traits that could foster innovation. For example, if restricting insider trading is simply part of the harmonization of policies contained in international trade agreements, then increases in trade or credit triggered by those agreements might drive innovation, not the restrictions on insider trading. We, however, find that neither international trade nor bank credit increases after countries start enforcing their insider trading laws, advertising the link between insider trading and innovation per se.

We next turn to our core analyses and test whether the cross-industry changes in innovation after the enforcement of insider trading laws are consistent with particular theoretical perspectives of how insider trading shapes innovation. In particular, we differentiate industries along two 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

[5] It is also worth noting that in studies of the determinants of insider trading laws, e.g., Beny (2013), 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.

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 all six of 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. In these 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 all time-varying industry characteristics that might confound our ability to draw sharp inferences about the relationship between insider trading and innovation. We also control for the interaction between each of the industry-specific traits and the levels of both economic and stock market development to further mitigate omitted variable concerns.

In terms of the estimated size of the impact, we find, for example, that citations to patents filed after a country first enforces its insider trading laws jump about 32% more in its industries that have above the median level of natural innovativeness 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., citations to patents filed after a country first enforces its insider trading laws increase 12% more than they rise in industries with naturally lower levels of intangible assets. Thus, insider trading restrictions are 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 also examine equity issuances. One mechanism through which enhanced valuations can spur innovation is by lowering the cost of capital. While Bhattacharya and Daouk (2002) show that restricting insider trading reduces the cost of capital in general, we examine whether it facilitates the flow of equity finance to innovative industries in particular. We find that both initial public offering and seasonal equity offering 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 total value of equity issuances increases 15% to 45% more in naturally innovative industries than it rises in other industries after a country starts enforcing its insider trading laws. These findings are consistent with the view that legal systems that protect outside investors from corporate insiders facilitate investment in technological innovation.

We conduct several additional robustness tests. First, we were concerned about omitted variables. For example, changes in financial policies or property rights protection at the same time that countries started enforcing their insider trading laws could affect the rate of innovation in certain industries and thereby prevent us from drawing correct inferences about insider trading from the industry-level analysis. Thus, we modify the control function approach described above and include interaction terms between industry opacity or industry innovativeness and indictors of securities market reforms, international capital flow policies, measures of bank regulatory and supervisory policies, the enactment of patent laws, intellectual property rights protection, property rights protection in general, and legal system effectiveness. All of the results hold. Similarly, time-invariant characteristics specific to an industry of a country might drive the results. Thus, we control for country-industry fixed effects to condition out these confounding factors and find that all of the results hold. We also implement Oster's (2016) omitted variable bias test and confirm our findings. Second, the results hold when examining different samples of countries or time periods. For example, the results are robust both to restricting the sample to only those countries that enforce their insider trading laws at some point during the sample period and to expanding the sample to all countries, even those that neither enact nor enforce insider-trading laws during the 1976-2006 period. The results also hold in industries with more patenting activities and in industries where patents are good indicators of the economic value and real output of innovation. Similarly, the results may be confounded by the formation of the European Union in the 1990s as the timing of enforcing insider trading law in some countries may be correlated with their pace of joining the European Union. We find that the results are robust to excluding EU countries that enforced insider-trading laws in the 1990s. Third, we provide additional evidence on the effects of the enforcement of insider trading laws on innovation. We find that the size of engineering workforce and the fraction of innovative industries increase after a country enforces its insider trading law. We discuss additional sensitivity analyses below.

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 start from the sample of countries that enacted insider trading laws during our sample period from 1976 to 2006. 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 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. This research suggests that the date the law is enforced—not the date that the law is enacted—signals the change of legal regime concerning insider trading. We examine both below. Based on the information provided in the online *Appendix A*, all the 74 countries with complete data had insider trading laws on their books by 2002, but only 29 of those 74 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, but the U.S. is not part of our sample.

In terms of the enactment and enforcement of insider trading laws, *Enact* equals one in the years after a country first enacts insider-trading laws and zero otherwise; *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. PATSTAT is updated biannually and we use the 2015 spring release, which has data through the end of the fifth week of 2015. PATSTAT 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 "subclass" to which each patent belongs (i.e., the International Patent Classification (IPC).[6,7]

Critically, we focus on the original invention, since some inventions are patented in multiple patent offices. Specifically, PATSTAT provides an identifier of each distinct "patent family", where a patent family includes all of the patents linked to a single invention. With this identifier, we identify the first time an invention is granted a patent and we call this the "original patent." Following the patent literature, we date patents using the application year of the original patent, rather than the actual year in which the patent is granted, because the application year is closer to the date of the invention (Griliches et al. 1987) and because the application year avoids varying delays between the application and grant year (Hall et al. 2001). We also use the original patent to (a) define the technological section and subclass(es) of the invention from its IPC and (b) record the country of residence of its primary assignee (i.e., owner) as the country of the invention.

We restrict the PATSTAT sample as follows. We only include patents filed with and

[6] 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.

[7] 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.

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 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.[8] After employing these restrictions and merging the patent data with the data on the enforcement of insider trading laws, we have a sample of 74 economies between 1976 and 2006.[9]

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 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

[8] 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.

[9] Our sample stops at 2006 to avoid any confounding effects from the global financial crisis.

PATSTAT IPCs into two-digit Standard Industrial Classifications (SICs),[10] which yields 47 unique industries at the two-digit SIC level. With respect to sampling criteria, our core sample excludes an industry from a country if no entities file patents in that industry throughout our sample period; if an industry starts to record patents in a specific country-year, then we treat all the subsequent years of the industry with no patent records as filing zero patents, and treat the years before the first recorded patent as missing.[11] 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, we also consider the extensive margin: Do more industries in a country engage in innovation? We find that the results hold on both the intensive and extensive margins.

We conduct our core analyses at the industry-country-year level, rather than at the firm level, because cross-country databases have very poor coverage of individual firms during our sample period. For example, the online platform of Orbis, only provides data since 2006, which is when our sample period ends.

We construct six 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*.[12] As emphasized above, we do everything at the invention—patent family—level and then convert the PATSTAT IPCs to two-digit SICs. As we make the conversion from the IPCs to the SICs using a weighted concordance scheme, our raw measure of patent count is not a discrete variable. Therefore, we do not use count models in our core, industry-level analyses, but we do provide count model assessment in country-level robustness tests noted below.[13]

---

[10] 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.

[11] The results are robust to treating these years before the first recorded patent as zeros.

[12] We follow the literature in using the natural logarithm of one plus the number of patents (e.g., Atanassov 2013, Fang et al, 2014, Cornaggia et al. 2014, Gao and Zhang 2016, Brav et al. 2017, and Mukherjee et al. 2017).

[13] Specifically, each IPC at subclass level is matched to a spectrum of ISICs with a probability weight attached to each mapping route. We first construct the patent count measure at IPC subclass level. Then, for each pair of IPC-ISIC, we multiply the patent count with the probability weight. Next, for each ISIC, we sum the weighted

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

Citation equals the natural logarithm of one plus the total number of citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. Thus, if a patent cites two patents on the same invention filed in different patent offices, we only count this as one citation. Similarly, if two patents in the same patent family each cites an invention, we only count this as one citation. As emphasized above, we seek to measure citations by inventions of other inventions and not double count such citations because of an invention being patented in multiple offices. As an invention—a patent family—may continue to receive citations for years beyond 2014, the last full year covered by the PATSTAT, we adjust for truncation bias using the method developed by Hall et al. (2001, 2005).[14] Then, we sum the citation counts over all patent families within each IPC subclass

---

patent counts at all the IPCs that are mapped to this ISIC. Thus, we obtain the patent count measure at ISIC level. Finally, we obtain the patent count measure at SIC level using the concordance scheme from ISICs to SICs.

[14] 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 $L = 0,1,\ldots,29,$ 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 $S_L^K = \sum_{\tau=0}^{L} P_\tau^K$, $L = 0,1,\ldots,29$, 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

and convert this to the two-digit SIC level for each industry *i*, in country *c*, and in year *t*.

PC Top 10% equals the natural logarithm of one plus the total number of highly-cited patents, where we define a patent as highly-cited if the total number of forward citations it receives falls into the top 10 percentiles of the citation distribution of all the patents that are filed in the same technology class and same year. We follow the approach in Balsmeier et al. (2017) and use this measure to evaluate the success of innovation. We first categorize a patent based on its position in the citation distribution for each IPC subclass, and each application year. After we identify the highly-cited patents, we count the number in each IPC subclass, each year, and then convert it to the two-digit SIC level.

Generality is a measure of the degree to which patents by each particular industry in a country *are cited by* patents in different 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.[15] Thus, a patent's generality value equals zero if the patent is only cited by other patents from a single IPC section. The generality value, therefore, 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. Following Hsu et al. (2014), we then sum the generality values of all patents within each IPC subclass, in each country, and each year. Finally, we convert this summed generality value, which is measured at the IPC subclass level, to SIC industries (using the method describe above) and take the natural logarithm of one plus this summed generality value at the SIC level to obtain an overall *Generality* measure at the industry-country-year level.

Originality is a measure of the degree to which patents by each particular industry in a

---

K and granted in 2006. We observe actual citations from $L=0$ to $L=8$ (i.e., for 9 years till the end of 2014). According to our calculations, these actual citations account for the share $\bar{S}_{L=8}^{K}$ of total citations of the patent in section *K* that was granted in 2006 over a 30-year lifetime. In this example, then, we multiply the actual sum of citations over the period 2006-2014 by the weighting factor of $1/\bar{S}_{L=8}^{K}$ to compute the adjusted total citations for the patent in section *K* and cohort 2006.

[15] Specifically, we follow the steps in Hall et al. (2001):

(1) For each patent *i*, we calculate c_i, the total number of patents citing patent *i*, and $c_{i,k}$, the number of patents belonging to IPC section *k* that cite patent *i*, where *k* is one of the N_i sections the patents citing patent *i* belong to (recall that there are eight IPC sections from "A" to "H");

(2) Then, for each patent *i* and IPC section *k*, we calculate $s_{i,k} = c_{i,k}/c_i$, which is the percentage of citations received by patent *i* that come from IPC section *k* over the total number of citations received by patent *i*;

(3) Next, for each patent *i*, we sum the squared percentage of citations from each IPC section *k* out of N_i sections to get the Herfindahl Index of the IPC sections ($\sum_k^{N_i} s_{i,k}^2$), and we use $1 - \sum_k^{N_i} s_{i,k}^2$ as the generality measure for patent *i*.

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.[16]

We also construct and use two variants of these measures. Specifically, *Patent Count**, *Patent Entities**, *Citation**, *PC Top 10%**, *Generality** and *Originality** equal the values of *Patent Count*, *Patent Entities*, *Citation*, *PC Top 10%*, *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 industry-country-year versions discussed above. 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}, *PC Top 10%* ^{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 online *Appendix A* provides more detailed information on the six patent-based indicators. In *Appendix A*, the patent-based measures are averaged over the sample period. *Patent Count** ranges from an average of 0.005 patents per industry-year in Tanzania to 468 per industry-year in Japan. The average number of truncation-adjusted citations for patents in an industry-year ranges from 0.02 in Tanzania 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 22 eventually-granted patents per year, while the standard deviation is as high as 148. *Citation** is also highly dispersed. In an average industry-country-year, the average value of *Citation** is 320 with a standard deviation of 3,223.

---

[16] *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.

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 six patent-based measures of innovation in industry *i*, of country *c*, in year *t*: *Patent Count*, *Patent Entities*, *Citation*, *PC Top 10%*, *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 contemporaneous events affecting all the 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 *Enact*, so that our analyses differentiate between putting insider trading laws on the books and actually enforcing those laws. 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. 2010) 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, but to summarize here we find the following. 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, banks, patent laws, property rights protection and legal integrity 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:

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

$Industry_i$ 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 also include the interaction between each industry trait and *Enact*, *GDP per capita*, and *Stock/GDP*, (i.e., *Industry X Enact*, *Industry X GDP per capita* and *Industry X Stock/GDP*), as well as *Export to US* in equation (2). These controls reduce concerns that the differential effects of time-varying, country-traits on the innovative activities in different industries confound the results. 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.[17]

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

[17] *Innovation Propensity* is computed after the U.S. first enforced its insider trading laws so that this natural innovativeness measure might capture some of the effects of enforcing insider trading restrictions across U.S. industries. Therefore, we take this measure as a sensitivity analysis of results on *High Tech* in examining the cross-industry response to the enforcement of insider trading laws.

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). 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, *High Tech* and *Intangibility* both equal to one in only 26% of industries, and the maximum correlation between either of the two natural innovativeness measures and the two natural opaqueness measures is less than 0.4. They are also conceptually distinct, as two industries might be equally opaque, but one might be more naturally innovative. For example, industries with the two-digit SIC codes “28” (Chemicals and Allied Products) and “47” (Transportation Services) both have above the median value of the intangibility measure (i.e., *Intangibility=1*), but the chemical industry had an average growth rate in R&D expenditures of 43% per annum, whereas the corresponding growth rate in the transportation services industry was only 3% during our sample period. 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. For instance, industries with two-digit SIC codes of "35" (Industrial and Commercial Machinery and Computer Equipment) and "32" (Stone, Clay, Glass, and Concrete Products) both have *High Tech=1* and *Innovation Propensity=1*, but the machinery industry is also classified as naturally opaque while the other is not. In this case, enforcement would have a bigger impact on valuations in the more opaque industry and therefore have a bigger impact on 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. *Figure 1* provides these two plots for $Citation^{c}$, where the plots include countries that enforce their insider trading laws at some point in the sample period. As portrayed in *Figure 1*, neither the level nor the rate of change in $Citation^{c}$ predicts the timing of the initial enforcement of insider trading laws. The plots for the other five patent-based measures yield similar results. 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}, *PC Top 10%*^{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.[18] 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) 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*) following Beny (2013).[19] As shown, while the lagged patent-based innovation measures often enter the enforcement regressions with negative coefficients, the estimated coefficients enter with t-statistics below 1.4 across all six specifications. That is, we cannot reject the hypothesis that the patent-based measures of innovation do not predict the timing of when countries start enforcing their insider trading laws.[20]

Third, we examine the dynamic relationship between innovation and the first time that a country enforces its insider trading laws. In *Figure 2*, we present a simple pre- and post-enforcement comparison of the patent-based measures of innovation. As with *Figure 1*, we use *Citation*^{c} for illustration and exclude countries in which insider-trading laws had not been enforced by the end of the sample period. For each country, we calculate the average citation counts received by the patents filed by its residents in year *t* over the pre- and post- enforcement period respectively. The pre- (post-)

[18] *Table 3* provides the results for the sample that includes both countries that enforced their insider trading laws during the sample period and those that did not. The same results hold when only including countries that enforced their laws during the sample period.

[19] *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).

[20] In robustness tests, we find that the growth rates of the innovation measures do not predict when a country starts enforcing its insider trading laws.

enforcement period is defined as the five years before (after) the enforcement of insider trading laws. Then, we calculate the average citation counts across countries for the pre- and post- enforcement period, and present the value in the bar chart.

Noticeably, there is a substantial increase in citation counts after an average country enforces the insider trading law. It rises from 18,611 to 31,778, amounting to a 71% increase. We find similarly sharp increase for the other five patent-based measures of innovation. While the evidence implies a positive correlation between enforcing insider trading laws and innovation, it does not warrant a casual inference if innovation has already been trending up before the enforcement of insider trading laws.

We next 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 specification on the same set of countries that enforced insider trading laws within our sample period as used for *Figure 1* and *Figure 2*:

$$Innovation_{c,t} = \alpha_0 + \sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau} Enforce_{c,t,\tau} + \delta_c + \delta_t + \varepsilon_{c,t}, \text{ where } \tau \neq 0. \qquad (3)$$

For illustrative purposes, we use $Citation^c$ to proxy for $Innovation_{c,t}$. $Enforce_{c,t,\tau}$ is a dummy variable that equals one if the observation at time t is τ years away from the year of initial law enforcement. If τ is greater than zero, then the dummy identifies the τ^{th} year after the initial enforcement of the insider trading laws; if τ is smaller than zero, it represents the τ^{th} year before the initial enforcement. We include a total of 15 dummies to trace out the year-by-year effect on innovation from at most 5 years before the event to at most 10 years afterwards. At the end points, all the years over 5 years before the initial enforcement and all the years beyond 10 years after the initial enforcement are excluded from the regression sample. The dummy variable for the year of initial enforcement is dropped from the regression. The regressions include country and year fixed effects. We first remove the pre-enforcement trend in the estimates from the 15-year estimation window and then subtract the pre-enforcement average of the estimates from each of the 15 coefficient estimates to center the figure. We then plot the centered coefficient estimates. We also include the 95% confidence interval based on robust standard errors. Thus, the confidence intervals evaluate whether each estimated parameter is significantly different from the pre-enforcement mean adjusted for any pre-enforcement trend.

Figure 3 illustrates the following. 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 3* depicts a 34% increase in $Citation^{c}$ after five years (from the centered value on the first enforcement date after adjusting for the pre-enforcement trend). 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 that carries onto the post-enforcement period. The overall pattern suggests that enforcing insider trading has an immediate and enduring simulative effect on innovation.

The fourth type of analysis of the validity and value of our empirical strategy employs 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 *Stock/GDP*, *Credit/GDP* or *Trade/GDP* as dependent variable. *Stock/GDP* measures the development of domestic stock market; *Credit/GDP* measures the development of domestic credit market; *Trade/GDP* gauges the intensity of international trade. *Figure 4* is plot in similar ways as *Figure 3*. As shown in *Figure 4*, neither the financial markets or the international trade changes in the same way that the patent-based indicators change after enforcement; indeed, none of *Stock/GDP*, *Credit/GDP* and *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 six 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 twelve model specifications. In all of the regressions reported throughout the main tables 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 twelve 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 broader set of control variables. The results indicate that the initial enforcement of insider trading laws is associated with a 15% increase in the number of patents (i.e., patenting intensity), a 12% increase in the number of patenting entities (i.e., scope of patenting activity), a 30% increase in citations (i.e., impact), a 11% increase in the number of highly-cited patents (i.e., breakthrough innovation measured by *PC Top 10%*), a 11% in generality score (i.e., breadth of impact on other technologies), and an 17% increase in originality score (i.e., breadth of other technologies cited).[21]

Consistent with earlier work emphasizing that the de facto change in the insider trading regime occurs when the laws are enforced, not when the laws are enacted, we find that *Enact* does not enter significantly. As reported in Panel B, 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*.

Following Bertrand and Schoar (2003) and Morse et al. (2016), we also evaluate the

[21] It is worth noting two points with respect to the estimated coefficients. First, since only some patents will be commercialized, the actual rate of improvement in productive technologies may be slower than the rate of increase in these patent-based metrics. Second, these estimated effects can be compared to other studies of how policies shape patenting. For example, Fang et al. (2014) find that when the U.S. shifted from the fractional pricing system to the decimal pricing system for some publicly traded firms, there was a 48% decrease in the number of patents for the treated firms relative to others. Cornaggia et al. (2014) find that when states removed restrictions on intrastate bank branching, there was a 31% drop in patents in the three years following deregulation.

explanatory power of the fixed effects to provide additional evidence on our empirical design. In unreported results, we find that the adjusted R-squared of 14.8% in the *Patent Count* model with only *Enforce* and year dummies as the regressors increases to 57.5% when including the full set of country and industry characteristics, and to 85.3% when also including country and industry fixed effects. The increase in the adjusted R-squared suggests that the addition of time-varying country and industry characteristics absorbs 42.7% additional variation in the rate of innovation and the addition of country and industry fixed effects leads to a further improvement of 27.8% of the variation explained over and above the time-varying country and industry characteristics. Moreover, the F-test shows that the set of control variables, country fixed effects and industry fixed effects are each jointly significant at the 1% significance level in the full model shown in Panel B of Table 4. These findings support our econometric design.

To address concerns that countries adopt packages of policy reforms at the same time 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, Harvey, and Lundblad (2005) for 54 countries in our sample, (10) *IPR Protection*, which measures the strength of intellectual property rights protection in particular, (11) *PR Protection*, which gauges the strength of property rights protection in general, (12) *Legal Integrity*, which evaluates the extent of impartiality of legal system and general observance of the law in a country, (13) *Contract Enforcement*, which measures effectiveness of contract enforcement, (14) *PR & Legal Index*, which measures the overall strength of legal and property rights protection, and is defined as the average of nine sub-indexes, including (10)-(13), (15) *Patent Law*, which equals one for the years after a country enacts its first patent law and zero before then; in column (16), we include *Financial Reform Index* in column (8), *PR & Legal Index* in column (14) and *Patent Law* in column (15) at the same time to control for aggregate policies on financial liberalization, property rights protection and legal environment. *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 96 regressions, as we examine each of the sixteen policy reform indicators for each of the six 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, separately or altogether, *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. For example, Saidi and Žaldokas (2017) find that firms patent less when they are more concerned about the cost of publicizing patents that reveal technological knowledge to their competitors. As patenting is a legal process whose benefits depends on the commitment to enforce patenting protections, stronger legal capacity and law enforcement in general may also lead to greater patent-based innovation. Therefore, it helps to isolate the effect of enforcing insider trading laws by controlling for the enactment of patent laws, measures of the enforcement of intellectual property rights, along with general measures of the property rights protection and contract enforcement.[22]

[22] Brown and Martinsson (2017) examine the relationship between corporate transparency and both R&D expenditures and *Patent Count*. One of their measures of corporate transparency is the enforcement of insider trading laws. They find that their measures of corporate transparency are robustly and positively linked with R&D expenditures and *Patent Count*. Our work is different. We do not examine corporate transparency in general; rather we focus on insider trading laws. Besides examining measures of the number, breadth, impact, generality, and originality of patents, as well as the other indictors of innovation discussed below, we assess whether the impact of the enforcement of insider trading laws on (a) patent-based measures of innovation and (b) the degree to which firms raise funds through equity issuances vary across industries in a theoretically

A related concern is that increases in patent count may result from higher patenting of existing technologies rather than new inventions. Thus, we analyze two alternative measures of innovation at country-level. The first measure is the size of engineering workforce in R&D, *Engineering Workforce,* which equals the number of technicians in R&D per one million people. We obtain the data from the WDI database of the World Bank. As the data coverage starts from 1996, we restrict the sample period of the regressions to 1996-2006. We use *ln(Engineering Workforce)* as the dependent variable and present the results in the first two columns of *Table 6*. In the first column, we use the full sample of countries where insider-trading laws were enacted within 1976-2006. In the second column, we exclude the countries where insider-trading laws were enforced by 1996 as *Enforce* stays at one for these countries during the sub-period of 1996-2006. Our results are robust to using both samples. As shown in column (2), the size of engineering workforce increases by 34% on average after a country enforces insider-trading laws. The second measure we use is the fraction of innovative industries in a country. We define innovative industries as follows. First, we calculate the average number of patents per firm for each industry-country-year.[23] Second, if the average number of patents per firm in an industry-country-year is in the top 25% (across the full sample of industry-country-year observations), we categorize this as an innovative industry. We then compute the fraction of innovative industries in each country-year and call this *Innovative Industry (top 25%)*. We follow a similar procedure to compute *Innovative Industry (top 10%)* for those industry-country-year observation in the top 10% of the full sample. We then use these country-year observations as dependent variable to assess whether the enforcement of insider trading laws is associated with a change in the proportion of innovative industries in a country. The results, as shown in column (3) and (4) in *Table 6*, show that the enforcement is associated with a statistically significant and material increase in the proportion of innovative industries. *Innovative Industry (top 25%)* increases by 3 percentage points after a country enforces insider trading law, which is 16% of the sample average.

We provide several additional robustness tests in an Online Appendix. First, we use alternative model specifications to address potential omitted variable bias in assessing the relationship between innovation and enforcement. In particular, we (a) control for country-industry fixed effects

predictable manner. Also, in focusing on intellectual property, we include controls for the legal enforcement of property rights in general, intellectual property rights in particular, and the patenting system even more particularly.

[23] For the number of firms in the calculation, we use the statistics from the Orbis database in 2006 as Orbis covers both public and private firms dating back to 2006 in the online platform.

and year fixed effects and (b) test for omitted variable bias using the procedure developed by Oster (2016). Panel A of *Appendix B* provides the results when controlling for country-industry and year fixed effects. 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 indicates that the results are not confounded by time-invariant characteristics specific to each industry in each country. Again, we find the adjusted R-squared increases from 14.8% to 96.2% (in the case of *Patent Count*) when we add country-industry fixed effects to the model with only time-varying controls and year dummies. We also implement Oster's (2016) test for omitted variable bias. As shown in the last column of Panel A, the test suggests that our findings are not influenced by omitted variables.[24]

Second, we cluster the standard errors at different levels to assess the sensitivity of the findings to different assumptions about the errors. Panel B of *Appendix B* provides the results when clustering at the industry and year level. The statistical significance increases materially. By clustering the standard errors at industry-level, we can control for within-industry correlations across countries. Panel C of *Appendix B* shows the results when standard errors are one-way clustered at country level. The results are robust to the alternative specification. Panel D of *Appendix B* reports the results when the standard errors are clustered at the country and industry level. This specification accounts for the correlation of observations within an industry or a country and the results hold when using this assumption about the errors. In Panel E of *Appendix B*, we show that the results are also robust to triple clustering the standard errors at the country, industry and year levels.

Third, we verify that the results hold when using a country-level sample. Since innovation is measured at industry-country-year level in *Table 4* and the enforcement of insider trading laws occurs at the country-year level, we were concerned that this could affect the results, even though we control for industry, country, and year fixed effects. Therefore, we reevaluate the impact of enforcing insider trading laws on innovation at country-year level in *Appendix C*. We control for *Enact*, *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP*, *Trade/GDP*, *Financial Reform Index*, *PR&Legal Index*, and *Patent*

[24] The Oster (2016) test statistic *delta* measures how important the omitted variables would have to be relative to the controlled ones to explain away the observed effect from the enforcement of insider trading laws (i.e., push *beta* estimate to zero). As controlled variables are typically more important in explaining the results from ex ante belief and collection efforts of the researchers, setting the cutoff of *delta* to one is recommended. We implement the test under the most stringent assumption that the model with a full control set has an R-squared of one, which, however, may understate the robustness of our results.

Law, the broadest set of control variables in the regressions and report t-statistics based on robust standard errors. As shown, all of the results hold at the country level. Furthermore, we use a Poisson model for the number of patents in column (1) of Appendix C as *Patent Count* is a strict count variable at the country-level. As shown, using the Poisson models does not alter the results.

Fourth, we exclude EU member countries that first enforced their insider trading laws in the 1990s. We perform this robustness test because some European countries started enforcing insider trading laws when the European Union was formed. We were concerned that participation into the European Union could stimulate innovation, confounding our interpretation of the regression results. *Appendix D* provides the results when excluding 11 countries, namely, Belgium, Czech Republic, Denmark, Finland, Germany, Greece, Hungary, Italy, Netherlands, Poland and Spain, which enforced insider trading laws in the 1990s and became EU members. The results are highly robust to excluding these countries. The estimated coefficients with *Enforce* have similar magnitudes and levels of significance across the six patent-based measures of innovation.

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), the first two panels in *Table 7* present 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 six regressions, where the dependent variable is one of the six patent-based measures. The explanatory variable of interest is the interaction terms, *High Tech X Enforce* in Panel A and *Innovation Propensity X Enforce* in Panel B, and the regressions also control for country-year and industry-year fixed effects, the interactions between respective industry traits and main control variables in the baseline regressions, 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, the number of patents increases approximately by 35% 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*, *PC Top 10%*, *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 X 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, the number of patents rises approximately by 41% 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.

We also examine the differential evolution of innovative activity in high- and low-tech industries before and after a country starts enforcing its insider trading laws. Specifically, we extend the dynamic regression in equation (3) to industry-level and modify it by interacting a series of time dummies with the categorization of whether industries are relatively "high-tech" or not, i.e., whether *High Tech* equals one or zero. We then estimate the following regression:

$$
\begin{aligned}
Innovation_{i,c,t} = \alpha_0 &+ \textstyle\sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau,i=h} (High\,Tech_i) \times Enforce_{c,t,\tau} \\
&+ \textstyle\sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau,i=l} (1 - High\,Tech_i) \times Enforce_{c,t,\tau} \\
&+ \lambda X'_{i,c,t} + \delta_c + \delta_t + \varepsilon_{c,t}, \text{ where } \tau \neq 0. \qquad (4)
\end{aligned}
$$

The estimated coefficients $\hat{\alpha}_{1,\tau,i=h}$ and $\hat{\alpha}_{1,\tau,i=l}$ provide information on the evolution of innovation in industries categorized as having high (i=h) and low (i=l) natural rates of innovation respectively. To depict the change of innovation in high-tech industries relative to that in low-tech industries, we adjust the coefficients in both groups by the fitted time trend on $\hat{\alpha}_{1,\tau,i=l}$. As in equation (3), we center the figure by subtracting the group-specific pre-enforcement mean from the trend-adjusted coefficients.

As shown in *Figure 5* for the case of *Citation*, there is a sharp break in the relative degree of innovation between high- and low-tech industries when countries start enforcing their insider trading laws. In the pre-enforcement period, innovative activities in the two groups almost overlap with each other, indicating parallel trends in the pre-enforcement period. After the country starts enforcing its insider trading laws, however, the high-tech industries experience a sharp increase in innovation while the other industries do not.

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 C—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 X Enforce* enters positively and significantly at the one percent level in the *Patent Count*, *Patent Entities*, *Citation*, *PC Top 10%, Generality*, and *Originality* regressions. Furthermore, the effect is large. Across the different patent-based measures of innovation, innovation increases by 12% to 16% more in opaque industries than in other industries after a country starts enforcing its insider trading laws.

Using the dummy variable defined on the standard deviation of the market-to-book ratio, *STD of MTB*, as an alternative proxy for informational opacity in Panel D, 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 X Enforce* enters positively and significantly in the *Patent Count*, *Patent Entities*, *Citation*, *PC Top 10%, Generality*, and *Originality* regressions, where the regressions continue to control for country-year effects, industry-year effects, the interactions between STD of MTB and time-varying, country-level traits (i.e., *STD of MTB X Enact*, *STD of MTB X GDP per capita*, and *STD of MTB X Stock/GDP*) 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.

4.2.3. Robustness tests

For all the regressions in *Table 7*, where industries are categorized by indicator variables, we perform a robustness check using continuous measures of industry traits. Panel A of *Appendix E* shows the summary statistics on the four continuous measures of industry traits, namely, *High Tech (cont.)*, *Innovation Propensity (cont.)*, *Intangibility (cont.)* and *STD of MTB (cont.)*. Panel B to Panel E of *Appendix E* present the regression results where industries are differentiated by the two measures of natural innovativeness and the two measures of natural opaqueness respectively. As can be seen from Panel B to Panel E of *Appendix E*, *Citation* increases significantly with the extent of natural innovativeness and natural opaqueness of an industry. For every one standard-deviation increase of *High Tech (cont.)* in an industry, the number of citations increases by 19% more after a country enforces the insider trading law. The results also hold for the other five patent-based measures of innovation.

To address the concern that industry-country specific policies may drive (1) the patterns of innovation and (2) the timing of the enforcement of insider trading laws, we examine the sensitivity of the *Table 7* results to including additional controls. In particular, we interact *High Tech*, *Innovation Propensity*, *Intangibility*, and *STD of MTB* with the full set of policy indicators used in *Table 5*. We confirm that all of the results in *Table 7* hold when adding these interaction terms and we present the results based on *High Tech* in *Table 8*. 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 X Enforce*, *Innovation Propensity X Enforce*, *Intangibility X Enforce*, and *STD of MTB X Enforce* continue to enter the innovation regressions positively and significantly with similar point estimates as those reported in *Table 7*. This evidence eases concerns that the cross-industry patterns of innovation and the enforcement of insider trading laws simply reflect these other policy changes. Again, we find that *Industry X Enact* does not enter the regressions significantly in any industry-partitioned analysis, which confirms that effective restrictions on insider trading start from enactment rather than enactment of insider trading laws.

To further address the concern that omitted, unobservable factors specific to an industry-country drive the results, we introduce country-innovative industry-year fixed effects into the regressions. Specifically, based on *Innovation Propensity*, we assign a value of one to an indicator variable corresponding to the group of innovative industries in a country-year, and zero otherwise. Similarly, we assign the value of one to another indicator variable corresponding to the group of non-innovative industries in a country-year, and zero otherwise. Since *Innovation Propensity X Enforce* is perfectly collinear with country-innovative industry-year indicators, we can include these country-innovative industry-year fixed effects only in the industry-level regressions partitioned by *High Tech*, *Intangibility* and *STD of MTB* respectively, and the results are shown in *Appendix F*. The results *High Tech X Enforce*, *Intangibility X Enforce*, and *STD of MTB X Enforce* are robust to the inclusion of these additional fixed effects that control for all contemporaneous changes in innovative industries in each country.

We push these analyses farther by testing whether industries in which insiders have a greater tendency to trade on insider information experience a more pronounced increase in innovation after a country starts enforcing insider trading laws. That is, are industries with a greater latent probability of insider trading more affected by restrictions on insider trading? To conduct this test, we construct three industry-level measures of the latent probabilities of insider trading based on U.S. industries. The first measure, *High IT*, equals one if the industry has above the median insider trading as measured by Thomson Reuters Insiders Data Feed.[25] The second measure of the probability of insider trading, *High PIN*, equals one if the industry has an above the median estimated probability of informed trading using an extended Easley et al (1996) model and zero otherwise.[26] The third measure, *High Price Vol*, equals one if the average price volatility of the firms in an industry is above the sample median and zero otherwise.[27] Intuitively, if insiders take advantages of private information to extract (and hide) trading profits, they are more likely to conduct trading when price volatility is high.

As shown in *Appendix G*, the results are consistent with the view that industries with a greater latent probability of insider trading experience a more pronounced increase in innovation after a country starts enforcing insider trading laws. More specifically, we use the interaction regression

[25] These trades are based on the U.S. Securities Exchange Commission (SEC) requirement that insiders file Form 4 to report their trading. We first calculate the average number of insider trades per firm in a two-digit SIC industry in a year. We then take the time-series average to obtain a measure of insider trading intensity for each industry. Since the data coverage starts from 1986, we calculate the time-series average from 1986 to 2006.

[26] We first obtain the annual measure of the Probability of Informed Trading (PIN) of each U.S. public firm. We retrieve the adjusted PIN measures from Duarte and Young (2009), which are available from 1983 to 2004 at: http://www.owlnet.rice.edu/~jd10/publications.html. The PIN equals the probability of information-based trading based on an extended version of Easley et al. (1996). We then calculate average PIN across the firms within each two-digit SIC industry in each year. We next take the time-series average to obtain the PIN measure for each industry. The indicator variable *High PIN* is set to one if the industry measure is above the sample median and zero otherwise.

[27] We obtain the stock prices of U.S. public firms from CRSP and adjust them to reflect the effect of stock splits and dividends. We calculate the standard deviation of the adjusted daily closing prices for each firm-year and scale it by the year-end adjusted closing price of the firm. We then take the average of the scaled measure within each two-digit SIC industry in a year and take the time-series average over the sample period for each industry to obtain the industry-level price volatility measure. We define *High Price Vol* as equal to one if the industry price volatility measure is above the sample median and zero otherwise.

specified by equation (2), where in this case *Industry* is one of the three measures of latent insider trading probabilities. Each of the interaction terms enters positively and significantly at the one percent level in each of the six patent-based innovation regressions.

Finally, we also test the sensitivity of the results to restricting the sample to only those countries that enforce their insider trading laws during the sample period. This reduces the sample by about 54%. Moreover, by excluding the countries where insider trading laws were not enforced within our sample period, we are comparing different industries in the same country and assessing whether they respond differently to the enforcement of the insider trading law. This means that the estimated effect of enforcement on innovation only reflects within-country variation and ignores comparisons with countries that have enacted, but not yet enforced, insider trading laws. Nevertheless, we confirm the core results. Panels A through D of *Appendix H*, provide the estimated coefficients on *High Tech X Enforce*, *Innovation Propensity X Enforce*, *Intangibility X Enforce*, and *STD of MTB X Enforce* respectively for each of the six patent-based proxies of innovation (i.e., it reports the results of 24 regressions). With the exception of two estimates (the *Patent Count* and *Patent Entities* estimates for *Intangibility X Enforce*), we continue to find that innovation increases significantly more in the naturally innovative and naturally opaque industries after a country enforces its insider trading law.

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 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 expected 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 or opaque 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*).

We first compare the simple average of pre- and post- enforcement equity issuance activities to obtain a preliminary estimate of the effect from enforcing insider trading laws. We use *Total Proceeds* for illustration and define the pre- (post-) enforcement period similarly as the five (ten) years before (after) the enforcement of insider trading laws. As shown in *Figure 6*, the average annual proceeds raised in a country increases from $1,882 million to $4,329 million. To obtain more accurate estimate, we use the following equation:

$$Equity\ Issuance_{i,c,t} = \beta_0 + \beta_1 Industry_i \times Enforce_{c,t} + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}. \quad (5)$$

Where $Equity\ Issuance_{i,c,t}$ is one of the nine measures of equity issuances and $Industry_i$ is *High Tech*, *Innovation Propensity*, *Intangibility* and *STD of MTB* respectively in Panel A to D in *Table 9*.

We continue to include country-year and industry-year fixed effects, the interactions between industry traits and the time-varying, country characteristics, and to control for the ratio of industry-country-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*). The first two panels of *Table 9* provide the regression results partitioned by the natural rate of innovation. Panel A provides the results from nine regressions in which the interaction term is *High Tech X Enforce*, while Panel B provides the results in which the interaction term is *Innovation Propensity X Enforce*.

As shown in *Table 9*, 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 *High Tech X Enforce* enters positively and significantly. The results are equally strong when examining the interaction term of *Innovation Propensity X Enforce* 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 Panel B estimates indicate that enforcing insider trading laws is associated with 26% larger increase in the proceeds from IPO in industries in which *Innovation Propensity* equals one than in industries in which *Innovation Propensity* equals zero. As another example, the reported estimates in Panel A suggest that when a country starts enforcing insider trading laws, this is associated with a 13% larger boost in the financing proceeds from SEO 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.

We obtain similar results in the regressions where industries are partitioned by the degree of information opacity. Panel C provides the results from nine regressions in which the interaction term is *Intangibility X Enforce*, while Panel D provides the results in which the interaction term is *STD of MTB X Enforce*. The interaction terms have positive and significant coefficients for all the nine measures of equity issuances, further advertising for the link between enforcing insider trading laws and innovation via removing information asymmetries.[28]

6. Robustness Tests

In this section, we conduct a battery of robustness tests to address other potential concerns with the analyses.

6.1. Alternative transformation of dependent variables

In our analyses, we follow the literature and use the natural logarithm of one plus the raw patent-based measures of innovation to avoid truncation due to zeros in the raw measures. The interpretation of the estimated coefficients as a percentage change, however, is not precise given the functional form. Thus, we now use the inverse hyperbolic sine transformation as an alternative way to construct the dependent variables. We redefine the six patent-based measures of innovation as follows. *Patent Count* = arcsinh(*Patent Count**) = $\ln\left(Patent\ Count^{*} + \sqrt{Patent\ Count^{*2} + 1}\right)$; *Patent Entities*, *Citation*, *PC Top 10%*, *Generality* and *Originality* are similarly transformed. We then redo the analyses using the newly transformed measures of innovation. As shown in columns (1) – (6) in the two panels of *Table 10*, the estimated effect from the enforcement of insider trading laws is significantly positive on all six patent-based measures of innovation and the economic magnitudes are similar to our core results.

To further alleviate the concern that zeros in the raw measures drive our results, we conduct the following two subsample analyses. First, we focus on the industries in the U.S. where there are more patents. Specifically, we calculate the total number of eventually-granted patents filed in each industry-year in the U.S., and take the time-series average of patent count within each industry as the measure of patenting intensity. Then, we rank all the observations in our sample by this measure and designate industries that rank above the median, in the top 25% and in the top10% as having high patenting activities respectively. We redo the baseline analysis based on the three subsamples and present the results in Panel A to C of *Appendix I*.[29] As shown, the positive effect of the enforcement

[28] The results in Table 9 are robust if we exclude the IPO bubble period from 1999 to 2001, or if we focus on the post 1985 period when the coverage of SDC database expands.

[29] As we have already focused on the high-patenting industries, the industry measure of innovativeness by *Innovation Propensity* does not have any variation in the subsamples of industries ranking in the top 25% and top 10% of patenting activities. Thus, we do not present the results of the cross-industry differential analyses. The results are robust, however, if we differentiate the industries by *High Tech*, *STD of MTB* or *Intangibility*.

of insider trading laws on innovation remains significant in these industries. Second, we restrict to the observations where the raw patent-based measures of innovation are greater than or equal to one and use the natural logarithm of these measures as our dependent variables. As shown in Panel D of *Appendix I*, the results remain statistically robust and exhibit similar magnitudes to our core analyses.

6.2. Weighted regressions by industry size

We were concerned that the results could be driven by a few industry-country-year observations with very little economic activity. As a robustness test, therefore, we employ a value-weighted model, in which we weight each industry-country-year observation by the total assets of firms in the country-industry.[30] We present the weighted regression results in columns (7) – (12) in the two panels of *Table 10*. The estimated effect is quantitatively similar to the equally-weighted regressions, which suggests that our core results are unlikely to be driven by industry-country observations with little economic activity.

6.3. Controlling for external financial dependence

We extend the analyses by examining (a) whether the results are robust to controlling for the possibility that the enforcement of insider trading laws exerts an especially large impact on industries that rely heavily on external finance and (b) whether external financial dependence is independently important in shaping the effect of enforcing insider-trading laws. We follow Rajan and Zingales (1998) in constructing a measure of external financial dependence (*EFD*),[31] where *EFD* equals one if its industry measure exceeds the sample median and zero otherwise. We employ the following regression specification:

$$Innovation_{i,c,t} = \beta_0 + \beta_1 Industry_i \times Enforce_{c,t} + \beta_2 EFD_i \times Enforce_{c,t} + \\ + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}, \qquad (6)$$

which augments equation (2) by including the interaction between *Enforce* and *EFD*. The matrix of

---

[30] We obtain the 2006 data from the Orbis database and take the natural logarithm of total assets as the weight. Our results are robust to weighting by the total number of firms, rather than the total assets of firms.

[31] We first calculate the dependence on external finance as the ratio of the external financing gap (i.e., capital expenditure in excess of cash flow from operation) over capital expenditure, averaged across all the U.S. public firms in each industry-year. We then take the time-series average at each two-digit SIC level as the measure of industry *EFD* for all the countries.

control variables includes *Industry X Enact, Industry X GDP per capita* and *Industry X Stock/GDP*, *EFD X Enact*, *EFD X GDP per capita*, *EFD X Stock/GDP* as well as *Export to US*, where *Industry* is one of our measures of the natural innovativeness or opaqueness of industries. We control for country-year and industry-year effects and cluster the standard errors at the country and year levels.

As shown in *Appendix J*, the interaction terms between *Enforce* and the four industry measures of natural innovativeness and opacity are robust to controlling for *EFD X Enforce*. This holds across each of the six patent-based innovation measures. Furthermore, *EFD X Enforce* enters with a positive and statistically significant coefficient in the regressions when we control for *Innovation Propensity X Enforce*, *Intangibility X Enforce*, or *STD of MTB X Enforce* in Panel B to D.

6.4. Patent-based indicators as proxies for innovation

As emphasized above, one potential challenge to interpreting patent-based indicators as measures of innovation is that an increase in the number of patents may merely reflect an increase in the patenting of existing technologies rather than new inventions. For the country-level analyses in *Table 6*, we used both the size of engineering workforce and the fraction of innovative industries as alternative dependent variables to address the concern. For industry-level analysis, we now use two other measures of innovation: (1) the economic value of patents based on the stock market reaction to patent grants (Kogan et al. 2016) and (2) the real output of innovation in terms of new product announcements (Mukherjee et al. 2017).[32] As these measures are mainly available for U.S. public firms, we cannot use them as dependent variables. However, we can use them to provide additional evidence on the links between the enforcement of insider trading laws and innovation.

In particular, we find industries for which the patent-based innovation measures are highly correlated with the Kogan et al (2016) and Mukherjee et al. (2017) innovation measures for U.S. firms. We then re-do our analyses only on these industries.[33] As shown in *Appendix K*, the results hold when

[32] Patent value data are obtained from the webpage of Noah Stoffman at https://iu.app.box.com/v/patents. Product announcement data are obtained from Alminas Žaldokas's webpage at http://www.alminas.com.

[33] Specifically, we implement the following strategy. First, we obtain the firm-level measures of patent value and product announcements from Kogan et al. (2016) and Mukherjee et al. (2017). Specifically, patent value in a firm-year is defined as the total dollar increase in a firm's market value contributed by patent issuances; the number of product announcements counts the number of product announcements whose announcement returns rank in the top 25% of the product-announcement sample in Mukherjee et al. (2017). Second, we aggregate the firm-level measures of patent value and product announcements to industry-level in each year, and combine the aggregated measures with the total number of patents produced by these firms in the same industry-year. Third, we calculate the time-series correlations between (1) the aggregated patent value and patent count, (2) the

using these strategies to focus on industries in which the patent-based indicators are especially good proxies for new innovations.

6.5. Robustness to multinational presence of industries

Finally, to address the concern that multinational firms may shift innovation across borders without much real effect on the domestic economy, we restrict the sample to those industries with little multinational presence in a country. We identify public firms as having a multinational presence if their listing countries are different from the domicile countries as recorded in Thomson Reuters's Worldscope database. Then we exclude the industries in which these firms operate and redo the analyses. As shown in *Appendix L*, our results hold using this subsample.

7. 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 80,000 industry-country-year observations across 74 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, our findings link with specific theories of how insider trading shapes innovation. First, several theories emphasize that insider trading dissuades other investors from expending resources on valuing innovative activities, which impedes the efficient allocation of capital to innovative endeavors. These theories predict that the enforcement of insider trading laws will 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. Second, to the extent that insider trading impedes

number of new product announcements and patent count within each industry over the years with data available in our sample period. As product announcement data start from 1990, we calculate the time-series correlation from 1990 to 2006. Then, we identify those industries where such correlations are above our sample median as industries whose patent count measures are highly correlated with (1) the market reaction to patent grants and (2) the number of new product announcements based on the work of these earlier studies. Thus, we find industries for which the patent-based innovation measures are highly correlated with other measures of innovation. We then re-do our analyses using only these industries.

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, especially among firm in naturally innovative industries. 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 reviewed by Levine (2005). 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.

References

Acharya, V, Baghai, R, Subramanian, K (2013) Labor laws and innovation. *Journal of Law and Economics* 56: 997-1037.

Acharya V, Subramanian K (2009) Bankruptcy codes and innovation. *Review of Financial Studies* 22:4949-4988.

Aggarwal A, Hsu D (2014) Entrepreneurial exits and innovation. *Management Science* 60: 867-887.

Amore M, Schneider C, Žaldokas A (2013) Credit supply and corporate innovation. *Journal of Financial Economics* 109:835-855.

Atanassov J (2013) Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. *The Journal of Finance* 68: 1097-1131.

Ayyagari M, Demirgüç-Kunt A, Maksimovic V (2011) Firm innovation in emerging markets: The role of finance, governance, and competition. *Journal of Financial and Quantitative Analysis* 46, 1545-1580.

Baker M, Wurgler J (2002) Market timing and capital structure. *Journal of Finance* 57:1-32.

Balsmeier B, Fleming L, Manso G (2017) Independent boards and innovation. *Journal of Financial Economics* 123: 536-557 .

Beck T, Clarke G, Groff A, Keefer P, Walsh P (2001) New tools in comparative political economy: The database of political institutions. *World Bank Economic Review* 15:165-176.

Beck T, Demirgüç-Kunt A, Levine R (2010) Financial institutions and markets across countries and over time-data and analysis. *World Bank Economic Review 24: 77-92.*

Beck T, Levine R, Loayza N (2000) Finance and the sources of growth. *Journal of Financial Economics* 58:261-300.

Bekaert G, Harvey C (2000) Foreign speculators and emerging equity markets. *Journal of Finance* 55: 565-613.

Bekaert G, Harvey C., Lundblad C (2005) Does financial liberalization spur growth? *Journal of Financial Economics* 77:3-55.

Benfratello L, Schiantarelli F, Sembenelli A (2008) Banks and innovation: Microeconometric evidence on Italian firms. *Journal of Financial Economics* 90:197-217.

Beny L (2013) The political economy of insider trading laws and enforcement: Law vs. politics? International evidence, in Stephen M. Bainbridge, eds.: *Research Handbook on Insider Trading* (Edward Elgar Publishing, Northampton).

Bertrand M, Schoar A (2003) Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics* 118:1169-1208.

Bhattacharya U, Daouk H (2002) The world price of insider trading. *Journal of Finance* 57:75-108.

Brav A, Jiang W, Ma S, Tian X (2017) How does hedge fund activism reshape corporate innovation? *Journal of Financial Economics* Forthcoming.

Brown J, Cookson A, Heimer R (2017) Law and finance matter: Lessons from externally imposed courts. *Review of Financial Studies* 30:1019-1051.

Brown J, Fazzari S, Petersen B (2009) Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance* 64:151-185.

Brown J, Martinsson G (2017) Does transparency stifle innovation? Evidence from R&D activity in different information environments. *Swedish House of Finance Research Paper* No. 15-16.

Brown J, Martinsson G, Petersen B (2012) Do financing constraints matter for R&D? *European Economic Review* 56:1512-1529.

Brown J, Martinsson G, Petersen B (2013) Law, stock markets, and innovation. *Journal of Finance* 68: 1517-1549.

Brown J, Martinsson G, Petersen B (2016) Stock markets, credit markets, and technology-led growth. *Journal of Financial Intermediation* Forthcoming.

Bushman R, Piotroski J, Smith A (2005) Insider trading restrictions and analysts' incentives to follow firms. *Journal of Finance* 60:35-66.

Chan L, Lakonishok J, Sougiannis T (2001) The stock market valuation of research and development expenditures. *Journal of Finance* 56:2431-2456.

Cornaggia J, Mao Y, Tian X, Wolfe B (2015) Does banking competition affect innovation? *Journal of Financial Economics* 115: 189-209.

DeMarzo P, Fishman M, Hagerty K (1998) The optimal enforcement of insider trading regulations. *Journal of Political Economy* 106:602-632.

Demsetz, H (1986) Corporate control, insider trading, and rates of return. *American Economic Review* 76:313-316.

Duarte J, Young L (2009) Why is pin priced? *Journal of Financial Economics* 91:119-138.

Easley D, Kiefer N, O'Hara M, Paperman J (1996) Liquidity, information, and infrequently traded stocks. *The Journal of Finance* 51:1405-1436.

Fang V, Tian X, Tice S (2014) Does stock liquidity enhance or impede firm innovation? *Journal of Finance* 69:2085-2125.

Fernandes N, Ferreira M (2009) Insider trading laws and stock price informativeness. *Review of Financial Studies* 22:1845-1887.

Fishman M, Hagerty K (1992) Insider trading and the efficiency of stock prices. *RAND Journal of Economics* 23:106-122.

Gao H, Zhang W (2016) Employment Nondiscrimination Acts and Corporate Innovation. *Management Science* Forthcoming.

Griliches Z, Pakes A, Hall B (1987) The value of patents as indicators of inventive activity., in Partha Dasgupta, and Paul Stoneman, eds.: *Economic policy and technical performance* (Cambridge University Press, London).

Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citation data file: Lessons, insights and methodological tools, *National Bureau of Economic Research Working Paper*.

Hall B, Jaffe A, Trajtenberg M (2005) Market value and patent citations. *RAND Journal of Economics* 36:16-38.

Harford J (2005) What drives merger waves? *Journal of Financial Economics* 77:529-560.

Holmstrom B (1989) Agency costs and innovation. *Journal of Economic Behavior and Organization* 12:305-327.

Hsu P, Tian X, Xu Y (2014) Financial development and innovation: Cross-country evidence. *Journal of Financial Economics* 112:116-135.

King R, Levine R (1993) Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics* 108:717-737.

Kogan L, Papanikolaou D, Seru A, Stoffman N (2017) Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics* 132: 665-712.

La Porta R, López de Silanes F, Shleifer A, Vishny R (1997) Legal determinants of external finance. *Journal of Finance* 52:1131-1150.

La Porta R, López de Silanes F, Shleifer A, Vishny R (1998) Law and finance. *Journal of Political Economy* 106:1113-1155.

Laeven L, Levine R, Michalopoulos S (2015) Financial innovation and endogenous growth. *Journal of Financial Intermediation* 24:1-24.

Leland H (1992) Insider trading: Should it be prohibited? *Journal of Political Economy* 100:859-887.

Levine R (2005) Finance and growth: Theory and evidence, in Philippe Aghion, and Steven N. Durlauf, eds.: *Handbook of Economics Growth* (Elsevier).

Levine R, Zervos S (1998) Stock markets, banks, and economic growth. *American Economic Review* 88:537-558.

Lybbert T, Zolas N (2012) Getting patents and economic data to speak to each other: An “algorithmic links with probabilities” approach for joint analyses of patenting and economic activity. *WIPO Economics & Statistics Working Paper Series*.

Manso G (2011) Motivating innovation. *Journal of Finance* 66:1823-1860.

Morse A, Wang W, Wu S (2016) Executive lawyers: gatekeepers or totems of governance. *Journal of Law and Economics* 59:847-888.

Mukherjee A, Singh M, Žaldokas A (2017) Do corporate taxes hinder innovation? *Journal of Financial Economics* 124:195-221.

Nanda R, Rhodes-Kropf M (2016) Financing risk and innovation. *Management Science* 63:901-918.

Oster E (2016) Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business and Economic Statistics* 1-18.

Park W (2008) International patent protection: 1960–2005. *Research Policy* 37:761-766.

Rajan R, Zingales L (1998) Financial dependence and growth. *American Economic Review* 88: 559-586.

Saidi F, Žaldokas A (2017) Patents as substitutes for relationships. *Working Paper*.

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.	Bhattacharya and Daouk (2002)
	Patent-based Innovation Measures	
Citation	The natural logarithm of one plus the total number of truncation-adjusted 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 residents of country *c*; truncation-adjusted citation count is first summed over all the patents in a particular IPC subclass, and then converted to two-digit Standard Industry Classification (SIC). Citation* is Citation before the log transformation. Citation^c is the natural logarithm of one plus the total number of truncation-adjusted forward citations made to (eventually granted) patents 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 residents of country *c*.	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 residents of 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, and then converted to two-digit SIC. 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 (eventually granted) patents 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 residents of country *c*.	PATSTAT Database
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 residents of 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, and then converted to two-digit SIC. 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 (eventually granted) patents 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 residents of country *c*.	PATSTAT Database
Patent Count	The natural logarithm of one plus the total number of (eventually-granted) patents in industry *i* that are filed with the patent offices in one of the 34 OECD countries and/or the EPO in year *t* by residents of country *c*; the total number of patents is first calculated at	PATSTAT Database

	IPC subclass level, and then converted to two-digit SIC. 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) patents 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 residents of country *c*.	
PC Top 10%	The natural logarithm of one plus the total number of (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 residents of country *c*, and that the total number of forward citations made to them fall into the top 10% of the citation distribution of all the patents in the same IPC subclass and application year. The number of top 10% cited patents is first counted at IPC subclass level, and then converted to two-digit SIC industry level. PC Top 10%* is PC Top 10% before the log transformation. PC Top 10%^{c} is the natural logarithm of one plus the total number of (eventually-granted) patents 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 residents of country *c*, and that the total number of forward citations to them fall into the top 10% of the citation distribution of all the patents filed in the same IPC subclass and application year.	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, and then converted to two-digit SIC. 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* with patent offices in one of the member countries of the Organization for Economic Cooperation and Development (OECD) and/or European Patent Office (EPO).	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 indicating fully repressed, 1 indicating partially repressed, 2 indicating largely liberalized and 3 indicating fully liberalized.	IMF
Central	The political orientation of the largest party in the government is central, i.e., centrist.	Database of Political Institution
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)
Contract Enforcement	An index that measures the strength of legal enforcement of contract, ranging from 0 (weakest) to 10 (strongest).	Fraser Institute

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
Engineering Workforce	The number of technicians in R&D per one million people in a country-year; data coverage starts from 1996.	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
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 real Gross Domestic Product (GDP) measured in 2005 U.S. dollar.	World Bank-WDI
GDP per capita	The natural logarithm of real GDP per capita measured in 2005 U.S. dollar.	World Bank-WDI
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
Innovative Industry (top 25%)	The fraction of innovative industries in a country-year; industries with the number of patents per firm ranked in the top 25% of the sample are categorized as innovative; we use the number of firms in 2006 for each industry in the calculation.	PATSTAT; Orbis
Innovative Industry (top 10%)	The fraction of innovative industries in a country-year; industries with the number of patents per firm ranked in the top 10% of the sample are categorized as innovative; we use the number of firms in 2006 for each industry in the calculation.	PATSTAT; Orbis
IPR Protection	An index that measures the strength of national intellectual property right (IPR) protection, ranging from 0 (weakest) to 5 (strongest); it is constructed as unweighted sum of the scores in five subcategories on patent rights, namely, coverage of patentability, membership in international treaties, duration of protection, enforcement mechanisms and restrictions on patent rights.	Park (2008)
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
Legal Integrity	An index that measures the strength and impartiality of the legal system, as well as popular observance of the law, ranging from 0 (weakest) to 10 (strongest).	Fraser Institute

Patent Law	An indicator variable equal to one in the years after a country enacts its first insider trading law, and equals zero otherwise	WIPO
Polity	A composite index indicating the level of democracy and autocracy, ranging from -10 (strongly autocratic) to 10 (strongly democratic).	Polity IV Database
PR & Legal Index	An index that measures the overall strength of legal system and property rights protection, ranging from 0 (weakest) to 10 (strongest); it is the average value over nine sub-indexes on: judicial independence, impartial courts, protection of property rights, military interference in rule of law and politics, integrity of the legal system, legal enforcement of contracts, regulatory restrictions on the sale of real property, reliability of police and business costs of crime.	Fraser Institute
PR Protection	An index that measures the strength of property rights (PR) protection, ranging from 0 (weakest) to 10 (strongest).	Fraser Institute
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 measure of the degree to which securities markets are liberalized. It codes on the measures a country has to encourage development of securities markets, including establishment of debt and equity markets, the auctioning of government securities, policies to encourage development of these markets, such as tax incentives or development of depository and settlement systems, development of derivatives market and institutional investor base, and policies on the openness of securities markets to foreign investors. The measure 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
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	
EFD	An indicator variable based on the external financial dependence (EFD) of each two-digit SIC industry; we first calculate the ratio of the difference between total capital expenditure (Compustat item *capx*) and cashflow from operation (sum of Compustat items *oancf*, *invch*, *recch*, *apalch*) over total capital expenditure for each public firm in the U.S., and take the average across the firms in each industry-year; we then calculate the time-series average within each industry over the sample period (1976-2006) as the EFD measure of the industry; EFD is set to 1 if it is above the sample median and 0 otherwise.	Compustat
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 IT	An indicator variable based on insider trading intensity of each two-digit SIC industry; we first calculate the number of insider trades per U.S. public firm in each industry-year; then we use the time-series average within each industry over the sample period with data available (1986-2006) as the measurement of insider trading intensity at industry level; High IT is set to 1 if it is above the sample median and 0 otherwise.	Thomson Reuters Insiders Data Feed (Form 4)
High PIN	An indicator variable based on the average Probability of Informed Trading (PIN) of each two-digit SIC industry; we first obtain the annual adjusted PIN measure for each U.S. public firm and take the average value across firms within each industry-year; then we use the time-series average within each industry over the sample period with data available (1983-2004) as the measurement of PIN at industry	Duarte and Young (2009)

	level; High PIN is set to 1 if it is above the sample median and 0 otherwise.	
High Price Vol	An indicator variable based on the average price volatility of each two-digit SIC industry; we first calculate the standard deviation of split-adjusted prices of each U.S. public firm in a year, scaled by its year-end split-adjusted price, and take the average value across firms within each industry-year; then we use the time-series average within each industry over the sample period (1976-2006) as the measurement of price volatility at industry level; High Price Vol is set to 1 if it is above the sample median and 0 otherwise.	CRSP
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. High Tech (cont.) is the continuous measure of high-tech intensiveness of an industry.	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. Innovation Propensity (cont.) is the continuous measure of innovation propensity of an industry.	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. Intangibility (cont.) is the continuous measure of industry intangibility.	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; STD of MTB is set to 1 if it is above the sample median and 0 otherwise. STD of MTB (cont.) is the continuous measure of the standard-deviation of market-to-book ratio in an industry.	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	SDC Platinum

	the two-digit SIC level.	
Proceeds per IPO	The natural logarithm of one plus the average amount of dollar proceeds per IPO (mil$) made in an industry- country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC Platinum
Proceeds per Issue	The natural logarithm of one plus the average amount of dollar proceeds per equity issuance (mil$) made in an industry-country-year; country is defined by the market place where the issuance is made; industry is defined at the two-digit SIC level.	SDC Platinum
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 truncation-adjusted citations to patent families in industry *i*, in country *c*, and in year *t*, where *t* is the application year. *PC Top 10%** is the total number of patents in industry *i*, country *c*, year *t*, whose number of forward citations fall into the top 10% of the citation distribution of all the patents in the same IPC subclass and application year. *Generality* and Originality** are the sum of the generality and originality scores, respectively of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. *Patent Count*, *Patent Entities*, *Citation*, *PC Top 10%*, *Generality* and *Originality* are the natural logarithm of one plus the respective values of *Patent Count**, *Patent Entities**, *Citation**, *PC Top 10%**, *Generality**, and *Originality**. *Patent Count^c*, *Patent Entities^c*, *Citation^c*, *PC Top 10%^{c}*, *Generality^c* and *Originality^c* are the natural logarithm of one plus the corresponding measure of innovation at country-year level. 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. Alternative measures of innovation at country-level include *ln(Engineering Workforce)* and the fraction of innovative industries in a country-year. 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 and legal 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*), information opacity (*Intangibility* and *STD of MTB*), insider trading probabilities (*High IT*, *High PIN*, and *High Price Vol*) and external financial dependence (*EFD*). 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.
Industry-level Patent-based Innovation Measures						
Patent Count*	83,200	0	22.3306	0.2038	25.6827	148.1828
Patent Entities*	83,200	0	17.8754	0.2654	27.3036	91.6897
Citation*	83,200	0	320.0123	0.8196	191.0646	3222.9220
PC Top 10%*	83,200	0	1.8666	0	1.2031	17.5865
Generality*	83,200	0	3.7720	0.0095	2.6566	31.2356
Originality*	83,200	0	4.0260	0.0141	3.0598	32.6387
Patent Count	83,200	0	0.9760	0.1855	3.2840	1.4866
Patent Entities	83,200	0	1.0155	0.2354	3.3430	1.4724
Citation	83,200	0	1.7482	0.5986	5.2578	2.2649
PC Top 10%	83,200	0	0.2547	0	0.7899	0.6879
Generality	83,200	0	0.3806	0.0094	1.2965	0.8694
Originality	83,200	0	0.4074	0.0140	1.4011	0.8989
Country-level Patent-based Innovation Measures						
Patent Count^c	2,083	0	3.1401	2.3979	7.2619	2.7661
Patent Entities^c	2,083	0	2.8299	2.0794	6.5596	2.4721
Citation^c	2,083	0	4.5297	4.2770	9.4744	3.5072
PC Top 10%^{c}	2,083	0	1.2958	0	4.3208	1.8964
Generality^c	2,083	0	1.7458	0.7282	4.9921	2.1359
Originality^c	2,083	0	1.8150	0.8280	5.2622	2.1745
Alternative Country-level Innovation Measures						
ln(Engineering Workforce)	282	4.4096	5.9745	6.2246	7.2616	1.1278
Innovative Industry (top 25%)	2,083	0	0.1864	0.0769	0.5957	0.2340
Innovative Industry (top 90%)	2,083	0	0.0742	0	0.2340	0.1389

Statistics	N	10th Percentile	Mean	Median	90th Percentile	Std. Dev.
Country-level Economic Factors						
Credit/GDP	1,939	0.2033	0.6721	0.5436	1.3085	0.4803
GDP	1,956	22.6792	24.8930	24.9870	27.0743	1.7051
GDP per capita	1,956	6.4873	8.6607	8.7185	10.4132	1.4212
Stock/GDP	1,988	0	0.2480	0.0612	0.7337	0.4550
Trade/GDP	1,943	0.3349	0.7673	0.6611	1.3271	0.4554
Country-level Policy Measures						
Credit Control	1,512	0	1.7842	2	3	1.0735
Interest Rate Control	1,512	0	2.1316	3	3	1.2063
Entry Barriers	1,512	0	1.9623	2	3	1.1570
Bank Supervision	1,512	0	0.9735	1	2	1.0170
Bank Privatization	1,512	0	1.2877	1	3	1.1219
Capital Control	1,512	0	1.8776	2	3	1.1018
Securities Market	1,512	0	1.8558	2	3	1.0615
Financial Reform Index	1,512	2	11.8729	13	19.5	6.1377
Liberal Capital Markets	1,589	0	0.5821	1	1	0.4934
IPR Protection	1,852	1.21	2.7797	2.89	4.33	1.1424
PR Protection	2,083	2.67	5.1776	4.93	7.65	1.8612
Legal Integrity	2,062	4.11	7.2311	6.96	10	2.4217
Contract Enforcement	2,083	3.06	5.0288	4.91	7.51	1.8214
PR & Legal Index	2,083	3.52	6.0703	6.18	8.37	1.8314
Patent Law	2,083	0	0.4004	0	1	0.4901
Country-level Legal and Political Factors						
Common Law	2,083	0	0.2876	0	1	0.4527
Polity	1,884	-7	4.8747	9	10	6.8386
Fractionalization	1,832	0.1376	0.5803	0.6348	0.8210	0.2433
Right	1,861	0	0.3837	0	1	0.4864
Central	1,861	0	0.1134	0	1	0.3171
Left	1,861	0	0.3541	0	1	0.4784
Industry-level characteristics						
Export to US	83,200	0	0.0178	0	0.0441	0.0575
High Tech	79,881	0	0.4903	0	1	0.4999
Innovation Propensity	79,630	0	0.4940	0	1	0.5000
Intangibility	83,200	0	0.4822	0	1	0.4997
STD of MTB	81,699	0	0.4973	0	1	0.5000
High IT	83,200	0	0.4985	0	1	0.5000
High PIN	79,691	0	0.4953	0	1	0.5000
High Price Vol	83,200	0	0.4978	0	1	0.5000
EFD	83,200	0	0.4773	0	1	0.4995
Industry-level Equity Issuance						
IPO Number	83,200	0	0.0488	0	0	0.2747
IPO Proceeds	83,200	0	0.1466	0	0	0.7961
Proceeds per IPO	83,200	0	0.1182	0	0	0.6462
SEO Number	83,200	0	0.0578	0	0	0.3098
SEO Proceeds	83,200	0	0.1777	0	0	0.9006
Proceeds per SEO	83,200	0	0.1429	0	0	0.7315
Total Issue Number	83,200	0	0.0911	0	0	0.3977
Total Proceeds	83,200	0	0.2681	0	0	1.1052
Proceeds per Issue	83,200	0	0.2096	0	0	0.8712

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 truncation-adjusted citations to patent families in country *c*, and in year *t*, where *t* is the application year. *PC Top 10%* ^{c} is the natural logarithm of one plus the total number of patents in country *c*, year *t*, whose number of forward citations fall into the top 10% of the citation distribution of all the patents in the same IPC subclass and application year. *Generality* ^{c} and *Originality* ^{c} are the natural logarithm of one plus the sum of the generality and originality scores, respectively of all the patents that are filed in year *t* by applicants from country *c*. We treat the countries where insider trading laws were not enforced within our sample period as always "at risk" of enforcing the law; for the countries where insider trading laws were enforced 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)	(6)
Patent Count [c]	-0.1300					
	(-1.32)					
Patent Entities [c]		-0.1154				
		(-1.01)				
Citation [c]			-0.0392			
			(-0.69)			
PC Top 10% [c]				-0.0440		
				(-0.54)		
Generality [c]					-0.0685	
					(-0.79)	
Originality [c]						-0.0121
						(-0.13)
Common Law	-0.1281	-0.1177	-0.0871	-0.0887	-0.0887	-0.0992
	(-0.58)	(-0.53)	(-0.40)	(-0.42)	(-0.42)	(-0.45)
Polity	-0.0008	-0.0014	-0.0072	-0.0080	-0.0070	-0.0083
	(-0.04)	(-0.07)	(-0.36)	(-0.40)	(-0.36)	(-0.40)
Fractionalization	-0.7041	-0.7561	-0.7343	-0.7246	-0.6976	-0.7489
	(-1.36)	(-1.39)	(-1.36)	(-1.33)	(-1.31)	(-1.36)
Right	-0.2406	-0.2412	-0.2426	-0.2092	-0.2062	-0.2302
	(-1.39)	(-1.38)	(-1.36)	(-1.19)	(-1.20)	(-1.32)
Central	0.3175	0.3482	0.3705	0.3637	0.3470	0.3649
	(1.01)	(1.11)	(1.18)	(1.18)	(1.13)	(1.16)
GDP	-0.1063	-0.1418	-0.2091**	-0.2180**	-0.1834*	-0.2463**
	(-0.89)	(-1.15)	(-2.53)	(-2.25)	(-1.69)	(-2.15)
GDP per capita	0.0361	0.0231	-0.0238	-0.0374	-0.0197	-0.0517
	(0.35)	(0.20)	(-0.24)	(-0.45)	(-0.23)	(-0.56)
Stock/GDP	-0.3430	-0.3453	-0.3029	-0.3085	-0.3114	-0.3053
	(-1.38)	(-1.33)	(-1.16)	(-1.22)	(-1.26)	(-1.18)
Credit/GDP	0.3964*	0.3657	0.3234	0.3235	0.3422	0.2895
	(1.75)	(1.58)	(1.48)	(1.49)	(1.57)	(1.28)
Observations	1,306	1,306	1,306	1,306	1,306	1,306
Controls	Yes	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: $\text{Innovation}_{\text{i,c,t}} = \alpha_0 + \alpha_1 \text{Enforce}_{\text{c,t}} + \gamma X'_{i,c,t} + \delta_{\text{c}} + \delta_{\text{i}} + \delta_{\text{t}} + \varepsilon_{\text{i,c,t}}$. *Enforce* is the key explanatory variable, which is equal to one for years after the insider trading law is enforced for the first time in a country. The dependent variable, *Innovation*, is one of the six 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. *PC Top 10%* is the natural logarithm of one plus the total number of patents in industry *i*, country *c*, year *t*, whose number of forward citations fall into the top 10% of the citation distribution of all the patents in the same IPC subclass and application year. *Generality* and *Originality* are the natural logarithm of one plus the sum of the generality and originality score, respectively, of all the patents in industry *i* that are filed in year *t* by applicants from country *c*. Control variables include *Enact*, *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	PC Top 10%	Generality	Originality
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.						
Enforce	0.2118**	0.1661**	0.3623***	0.1338***	0.1214***	0.2235***
	(2.68)	(2.12)	(2.84)	(3.71)	(3.27)	(4.09)
Controls	No	No	No	No	No	No
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,200	83,200	83,200	83,200	83,200	83,200
Adjusted R-squared	0.839	0.848	0.847	0.719	0.762	0.760
Panel B.						
Enforce	0.1547**	0.1186*	0.2948**	0.1094***	0.1059***	0.1679***
	(2.44)	(1.94)	(2.59)	(3.50)	(3.43)	(3.58)
Control variables:						
Enact	0.0098	0.0109	-0.0262	-0.0022	0.0034	-0.0174
	(0.25)	(0.28)	(-0.51)	(-0.19)	(0.25)	(-0.94)
GDP	-0.0011	0.0525	-0.1834	-0.2136	-0.1061	-0.4966**
	(-0.00)	(0.21)	(-0.37)	(-1.63)	(-0.80)	(-2.66)
GDP per capita	0.4602**	0.4593**	1.1689***	0.3020**	0.3436***	0.6895***
	(2.29)	(2.40)	(2.95)	(2.71)	(3.20)	(4.28)
Stock/GDP	0.1225**	0.0970*	0.2347**	0.0791***	0.0643*	0.1097***
	(2.15)	(1.73)	(2.22)	(2.76)	(1.91)	(2.78)
Credit/GDP	0.1155	0.0995	0.2213	0.0236	0.0210	0.0501
	(1.58)	(1.34)	(1.60)	(0.48)	(0.46)	(0.88)
Export to US	1.2157***	1.0647***	1.4617***	0.8264***	0.9999***	0.9820***
	(6.21)	(6.58)	(6.20)	(4.69)	(5.16)	(5.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,561	76,561	76,561	76,561	76,561	76,561
Adjusted R-squared	0.853	0.862	0.861	0.728	0.771	0.773

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 related to financial liberalization, property rights protection and general legal enforcement. We follow the following specification: $\text{Innovation}_{i,\text{c,t}} = \alpha_0 + \alpha_1 \text{Enforce}_{\text{c,t}} + \alpha_2 \text{Policy}_{c,t} + \lambda X'_{i,c,t} + \delta_\text{c} + \delta_\text{i} + \delta_\text{t} + \varepsilon_{i,\text{c,t}}$. *Enforce* is equal to one for years after the insider trading law is enforced for the first time in a country. We use an assortment of *Policy* measures from columns 1) to 16), among which 1) – 9) correspond to financial liberalization, 10) – 15) correspond to property rights protection, 16) corresponds to two composite indexes on financial liberalization and property rights protection. 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 Contro*l 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 55 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 54 countries in our sample; 10) *IPR Protection* is an index measuring the strength of national intellectual property rights (IPR) protection, ranging from 0 (weakest) to 5 (strongest); it is obtained from Park (2008) for 63 countries in our sample; 11) *PR protection* is an index measuring the strength of property rights protection, ranging from 0 (weakest) to 10 (strongest); 12) *Legal Integrity* is an index measuring the strength and impartiality of legal system and the popular observance of the law, ranging from 0 (weakest) to 10 (strongest); 13) *Contract Enforcement* is an index measuring the strength of legal contract enforcement, ranging from 0 (weakest) to 10 (strongest); 14) *PR & Legal Index* measures the overall strength of legal system and property rights protection, ranging from 0 (weakest) to 10 (strongest); it is the average value over nine sub-indexes on: judicial independence, impartial courts, protection of property rights, military interference in rule of law and politics, integrity of the legal system, legal enforcement of contracts, regulatory restrictions on the sale of real property, reliability of police and business costs of crime; Variables in columns 11)-14) are obtained from Fraser Institute for a maximum of 74 countries in our sample; 15) *Patent Law* is set equal to one after a country enacted the first patent law and zero otherwise; we obtain the year of patent law enactment from WIPO; Column (16) includes *Financial Reform Index*, *PR & Legal Index* and *Patent Law* in the regression. The dependent variable, *Innovation*, is one of the six patent-based measures of innovation defined as the natural logarithm of one plus the raw measure. Control variables include *Enact*, *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.

	Credit Control	Interest Rate Control	Entry Barriers	Bank Supervision	Bank Privatization	Capital Control	Securities Market	Financial Reform Index	Liberal Capital Markets	IPR Protection	PR Protection	Legal Integrity	Contract Enforcement	PR & Legal Index	Patent Law	Fin. Reform; PR&Legal; Patent Law
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A. Patent Counts																
Enforce	0.1519**	0.1531**	0.1532**	0.1532**	0.1471**	0.1478**	0.1526**	0.1490**	0.1961***	0.1843***	0.1576**	0.1634**	0.1538**	0.1563**	0.1549**	0.1534**
	(2.43)	(2.45)	(2.62)	(2.43)	(2.52)	(2.33)	(2.50)	(2.44)	(3.21)	(2.90)	(2.50)	(2.60)	(2.42)	(2.47)	(2.43)	(2.66)
Panel B. Patent Entities																
Enforce	0.1165*	0.1172*	0.1174**	0.1173*	0.1117*	0.1125*	0.1160*	0.1135*	0.1606**	0.1470**	0.1216*	0.1272**	0.1186*	0.1201*	0.1188*	0.1185**
	(1.96)	(1.97)	(2.10)	(1.95)	(2.01)	(1.84)	(2.00)	(1.94)	(2.75)	(2.39)	(2.01)	(2.10)	(1.94)	(1.97)	(1.94)	(2.14)
Panel C. Citations																
Enforce	0.3113***	0.3110***	0.3114***	0.3143***	0.3071***	0.3169***	0.3038***	0.3108***	0.3252**	0.3766***	0.2976**	0.3125***	0.2914**	0.2919**	0.2957**	0.3114***
	(3.03)	(3.03)	(3.16)	(3.08)	(3.06)	(3.03)	(3.09)	(3.01)	(2.60)	(3.42)	(2.63)	(2.86)	(2.59)	(2.52)	(2.58)	(2.95)
Panel D. PC Top 10%																
Enforce	0.0939***	0.0942***	0.0943***	0.0938***	0.0929***	0.0920***	0.0957***	0.0927***	0.1171***	0.1132***	0.1098***	0.1113***	0.1082***	0.1095***	0.1092***	0.0937***
	(3.01)	(3.05)	(3.10)	(3.05)	(3.05)	(2.98)	(3.09)	(3.07)	(3.55)	(3.77)	(3.56)	(3.55)	(3.48)	(3.51)	(3.52)	(3.09)
Panel E. Generality																
Enforce	0.1005***	0.1008***	0.1008***	0.1005***	0.0991***	0.0993***	0.1005***	0.0996***	0.1220***	0.1184***	0.1073***	0.1088***	0.1058***	0.1068***	0.1060***	0.1001***
	(3.29)	(3.32)	(3.36)	(3.32)	(3.38)	(3.24)	(3.33)	(3.30)	(3.76)	(3.78)	(3.54)	(3.54)	(3.41)	(3.48)	(3.43)	(3.34)
Panel F. Originality																
Enforce	0.1255**	0.1255**	0.1261**	0.1252**	0.1243**	0.1238**	0.1282**	0.1234**	0.1773***	0.1663***	0.1696***	0.1704***	0.1662***	0.1680***	0.1675***	0.1266**
	(2.63)	(2.67)	(2.67)	(2.63)	(2.62)	(2.59)	(2.66)	(2.65)	(3.71)	(3.56)	(3.70)	(3.67)	(3.58)	(3.59)	(3.61)	(2.74)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6 Insider Trading Law Enforcement and Alternative Measures of Innovation

This table provides evidence to the baseline results using alternative measures of innovation at country level. We use the following specification to perform the analysis: $\text{Innovation}_{c,t} = \alpha_0 + \alpha_1 \text{Enforce}_{c,t} + \gamma X'_{c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$. *Enforce* is equal to one for years after the insider trading law is enforced for the first time in a country. The dependent variable, *Innovation*, is evaluated as *ln(Engineering Workforce)* in columns (1)-(2) and as the fraction of innovative industries in columns (3)-(4). *Engineering Workforce* is defined as the number of technicians in R&D for every one million people of a country in a year. As the number of technician is available from World Bank WDI database since 1996, the sample period for column (1) and (2) is from 1996 to 2006. Columns (1) is based on the full sample of countries with enactment of insider trading laws between 1976 and 2006. Columns (2) is based on the sub-sample of countries where insider trading laws were not yet enforced by 1996. We define an industry as innovative in a country-year if the average number of patents per firm in the industry is ranked above the 75^{th} percentile or the 90^{th} percentile of the sample, we then calculate the fraction of innovative industries in each country-year by the two cutoffs as *Innovative Industry (top 25%)* and *Innovative Industry (top 10%)* respectively. Control variables include *Enact*, *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Trade/GDP*. Table 1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on heteroskedasticity-robust standard errors. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variable	ln(Engineering Workforce)		Innovative Industry (top 25%)	Innovative Industry (top 10%)
	(1)	(2)	(3)	(4)
Enforce	0.2460***	0.3422***	0.0291***	0.0230***
	(2.63)	(3.20)	(4.62)	(6.52)
Controls	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	275	155	1,867	1,867
Adjusted R-squared	0.963	0.963	0.943	0.951
Sample	Full	Enforce after 96	Full	Full

Table 7 Insider Trading Law Enforcement and Innovation: Cross-industry Heterogeneous Reponses

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 and different degrees of opacity. We use the following specifications: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{Industry}_i \times \text{Enforce}_{\text{c,t}} + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$, where *Industry* is *High Tech*, *Innovation Propensity*, *Intangibility* and *STD of MTB* respectively in Panel A, B, C, D. *Enforce* is a dummy variable set equal to one for years after the insider trading 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. *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 six patent-based measures of innovation defined as the natural logarithm of one plus the raw measure. Control variables include *Industry* × *Enact*, *Industry* × *GDP per capita*, *Industry* × *Stock/GDP*, *Export to US*, *Industry* is *High Tech*, *Innovation Propensity*, *Intangibility* and *STD of MTB* respectively in Panel A, B, C, D. 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)	PC Top 10% (4)	Generality (5)	Originality (6)
Panel A.						
High Tech×Enforce	0.3491***	0.3158***	0.3245***	0.2397***	0.2900***	0.3039***
	(4.92)	(4.95)	(3.72)	(3.48)	(3.73)	(4.01)
Observation	75,542	75,542	75,542	75,542	75,542	75,542
Adj. R-squared	0.875	0.884	0.888	0.751	0.794	0.805
Panel B.						
Innovation Propensity×Enforce	0.4122***	0.3833***	0.3107***	0.3004***	0.3581***	0.3728***
	(4.69)	(4.61)	(3.21)	(3.59)	(3.89)	(4.11)
Observation	75,310	75,310	75,310	75,310	75,310	75,310
Adj. R-squared	0.880	0.889	0.890	0.760	0.803	0.812
Panel C.						
Intangibility×Enforce	0.1579***	0.1425***	0.1197**	0.1455***	0.1360***	0.1468***
	(4.77)	(4.73)	(2.70)	(3.82)	(3.97)	(4.39)
Observation	78,662	78,662	78,662	78,662	78,662	78,662
Adj. R-squared	0.869	0.878	0.882	0.740	0.779	0.790
Panel D.						
STD of MTB×Enforce	0.1265***	0.1028**	0.1551**	0.1260***	0.1589***	0.1553***
	(2.98)	(2.55)	(2.59)	(3.94)	(4.31)	(4.36)
Observation	77,252	77,252	77,252	77,252	77,252	77,252
Adj. R-squared	0.870	0.880	0.884	0.745	0.788	0.798
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 Insider Trading Law Enforcement and Innovation: Controlling for Differential Effect of Policies across Industries

This table presents the industry-level partitioned regression results, controlling for the interaction between industry categorization and each of the set of policy changes on financial liberalization and property rights protection. We follow the specification: $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1 \text{High Tech}_i \times \text{Enforce}_{\text{c,t}} + \beta_2 \text{High Tech}_i \times \text{Policy}_{c,t} + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$. We interact *High Tech* with an assortment of *Policy* measures from columns 1) to 16), among which 1) – 9) correspond to financial liberalization, 10) – 15) corresponds to property rights protection, 16) corresponds to *Financial Reform Index*, *PR & Legal Index* and *Patent Law*. The dependent variable, *Innovation*, is one of the six patent-based measures of innovation defined as the natural logarithm of one plus the raw measure from panel A to F. Control variables include *High Tech × Enact*, *High Tech × GDP per capita*, *High Tech × Stock/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.

Control variables:	Enforce×															
	Credit Control	Interest Rate Control	Entry Barriers	Bank Supervision	Bank Privatization	Capital Control	Securities Market	Financial Reform Index	Liberal Capital Markets	IPR Protection	PR Protection	Legal Integrity	Contract Enforcement	PR & Legal Index	Patent Law	Fin. Reform; PR&Legal; Patent Law
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A. Dep.=Patent Counts																
High Tech×Enforce	0.2339***	0.2346***	0.2272***	0.2278***	0.2336***	0.2339***	0.2257***	0.2349***	0.3102***	0.2746***	0.3278***	0.3406***	0.3531***	0.3491***	0.3108***	0.1972***
	(3.39)	(3.35)	(3.34)	(3.10)	(3.31)	(3.34)	(3.32)	(3.37)	(3.78)	(4.41)	(4.69)	(4.82)	(5.02)	(5.02)	(4.50)	(3.07)
Panel B. Dep.=Patent Entities																
High Tech×Enforce	0.1951***	0.1956***	0.1886***	0.1869***	0.1942***	0.1951***	0.1876***	0.1957***	0.2758***	0.2418***	0.2955***	0.3076***	0.3190***	0.3158***	0.2796***	0.1594**
	(3.08)	(3.06)	(3.05)	(2.86)	(3.05)	(3.07)	(3.06)	(3.06)	(3.82)	(4.23)	(4.77)	(4.85)	(5.11)	(5.09)	(4.41)	(2.70)
Panel C. Dep.=Citations																
High Tech×Enforce	0.2309**	0.2282**	0.2190**	0.2228**	0.2378**	0.2286**	0.2201**	0.2297**	0.2981***	0.2557***	0.2978***	0.3154***	0.3283***	0.3245***	0.2661***	0.1645**
	(2.55)	(2.51)	(2.55)	(2.39)	(2.56)	(2.51)	(2.47)	(2.52)	(2.86)	(3.02)	(3.65)	(3.63)	(3.85)	(3.80)	(3.19)	(2.07)
Panel D. Dep.=PC Top 10%																
High Tech×Enforce	0.1736**	0.1735**	0.1665**	0.1734**	0.1696**	0.1730**	0.1678**	0.1731**	0.2893***	0.2067***	0.2230***	0.2372***	0.2405***	0.2397***	0.2080***	0.1405**
	(2.69)	(2.60)	(2.58)	(2.49)	(2.47)	(2.60)	(2.54)	(2.62)	(3.75)	(3.33)	(3.36)	(3.46)	(3.45)	(3.51)	(3.30)	(2.33)
Panel E. Dep.=Generality																
High Tech×Enforce	0.1995**	0.1985**	0.1901**	0.1950**	0.1964**	0.1976**	0.1905**	0.1992**	0.3411***	0.2375***	0.2670***	0.2860***	0.2916***	0.2900***	0.2491***	0.1579**
	(2.68)	(2.58)	(2.55)	(2.45)	(2.49)	(2.58)	(2.51)	(2.61)	(3.95)	(3.46)	(3.61)	(3.70)	(3.73)	(3.79)	(3.48)	(2.28)
Panel F. Dep.=Originality																
Enforce×High Tech	0.2041**	0.2035**	0.1953**	0.1990**	0.2021**	0.2030**	0.1961**	0.2042**	0.3454***	0.2487***	0.2808***	0.2996***	0.3057***	0.3039***	0.2656***	0.1663**
	(2.75)	(2.67)	(2.66)	(2.52)	(2.62)	(2.68)	(2.61)	(2.70)	(4.03)	(3.69)	(3.91)	(3.97)	(4.01)	(4.08)	(3.75)	(2.45)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 9 Insider Trading Law Enforcement and Equity Issuance: Cross-industry Heterogeneous Reponses

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 rate of innovation and natural opacity. 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: $\text{Equity Issuance}_{i,\mathrm{c,t}} = \beta_0 + \beta_1 \text{Industry}_i \times \text{Enforce}_{\mathrm{c,t}} + \lambda X'_{i,c,t} + \delta_{\mathrm{c,t}} + \delta_{i,\mathrm{t}} + \varepsilon_{i,\mathrm{c,t}}$. *Enforce* is a dummy variable set equal to one for years after the insider trading law is enforced for the first time in a country. 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. Control variables include *Industry × Enact*, *Industry × GDP per capita*, *Industry × Stock/GDP*, *Export to US*, where *Industry* is *High Tech*, *Innovation Propensity*, *Intangibility*, and *STD of MTB* respectively in Panel A, B, C, D. Table 1 provides detailed definitions of the variables. Robust t-statistics are reported in parenthesis, which are based on standard errors clustered at country and year level. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

Dependent variables	IPO Number (1)	IPO Proceeds (2)	Proceeds per IPO (3)	SEO Number (4)	SEO Proceeds (5)	Proceeds per SEO (6)	Total Issue Number (7)	Total Proceeds (8)	Proceeds per Issue (9)
Panel A.									
High Tech×Enforce	0.0580***	0.1288**	0.0847**	0.0686***	0.1328**	0.0789*	0.0895***	0.1527**	0.0782*
	(2.90)	(2.33)	(2.12)	(2.95)	(2.54)	(2.03)	(3.12)	(2.37)	(1.72)
Observations	75,542	75,542	75,542	75,542	75,542	75,542	75,542	75,542	75,542
Adj. R-squared	0.382	0.316	0.287	0.421	0.322	0.262	0.473	0.387	0.324
Panel B.									
Innovation Propensity×Enforce	0.1027***	0.2649***	0.1867***	0.1367***	0.3707***	0.2631***	0.1783***	0.4482***	0.2998***
	(3.13)	(2.91)	(2.94)	(3.61)	(3.93)	(3.96)	(3.75)	(3.85)	(3.83)
Observations	75,310	75,310	75,310	75,310	75,310	75,310	75,310	75,310	75,310
Adj. R-squared	0.389	0.323	0.292	0.432	0.335	0.274	0.484	0.400	0.333
Panel C.									
Intangibility×Enforce	0.0603**	0.1386**	0.0889**	0.0553**	0.1308**	0.0806**	0.0814**	0.1689**	0.0944*
	(2.35)	(2.14)	(2.09)	(2.34)	(2.24)	(2.12)	(2.55)	(2.27)	(1.99)
Observations	78,662	78,662	78,662	78,662	78,662	78,662	78,662	78,662	78,662
Adj. R-squared	0.373	0.308	0.279	0.408	0.312	0.255	0.461	0.377	0.316
Panel D.									
STD of MTB×Enforce	0.0964***	0.2743***	0.1978***	0.1134***	0.3151***	0.2200***	0.1556***	0.4100***	0.2745***
	(3.61)	(3.62)	(3.75)	(3.46)	(3.75)	(3.61)	(3.86)	(4.13)	(4.11)
Observations	77,252	77,252	77,252	77,252	77,252	77,252	77,252	77,252	77,252
Adj. R-squared	0.383	0.318	0.287	0.422	0.325	0.265	0.475	0.390	0.326
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

Table 10 Insider Trading Law Enforcement and Innovation:
Robustness to Alternative Transformation of Innovation Measures and Weighted Regressions

This table presents two robustness tests. The first examines the effect of the enforcement of insider trading laws on inverse hyperbolic sine transformed innovation measures (columns (1)-(6)); the second uses weighted regressions by the total assets of firms in a country-industry in 2006 (columns (7)-(12)). We use the natural logarithm of total assets as the specific weight for each country-industry. We use the specification: $\text{Innovation}_{i,\text{c,t}} = \alpha_0 + \alpha_1\text{Enforce}_{\text{c,t}} + \alpha_2\text{Enforce}_{c,t} + \lambda X'_{i,c,t} + \delta_\text{c} + \delta_\text{i} + \delta_\text{t} + \varepsilon_{i,\text{c,t}}$ in Panel A and $\text{Innovation}_{i,\text{c,t}} = \beta_0 + \beta_1\text{Industry}_i \times \text{Enforce}_{\text{c,t}} + \lambda X'_{i,c,t} + \delta_{\text{c,t}} + \delta_{i,\text{t}} + \varepsilon_{i,\text{c,t}}$ in Panel B. *Enforce* is equal to one for years after the insider trading law is enforced for the first time in a country. *Innovation* is evaluated as patent-based measures after the inverse hyperbolic sine transformation in columns (1)-(6) and as the natural logarithm of one plus the raw value of the patent-based measures in columns (7)-(12). Control variables include *Enact*, *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US* in Panel A and include *Industry* × *Enact*, *Industry* × *GDP per capita*, *Industry* × *Stock/GDP*, *Export to US*, where *Industry* is *High Tech*, *Innovation Propensity*, *Intangibility* and *STD of MTB* respectively in Panel B. 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.

Panel A.

	Inverse Hyperbolic Sine Transformation						Weighted Regressions					
Dependent variable	Patent Count	Patent Entities	Citation	PC Top 10%	Generality	Originality	Patent Count	Patent Entities	Citation	PC Top 10%	Generality	Originality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Enforce	0.1644**	0.1245*	0.2962**	0.1332***	0.1253***	0.1983***	0.1671**	0.1230*	0.2710***	0.1172***	0.1224***	0.1644***
	(2.23)	(1.75)	(2.36)	(3.50)	(3.36)	(3.53)	(2.54)	(1.95)	(2.86)	(3.54)	(3.73)	(3.24)
Observations	76,561	76,561	76,561	76,561	76,561	76,561	55,352	55,352	55,352	55,352	55,352	55,352
Adjusted R-squared	0.861	0.870	0.862	0.733	0.778	0.780	0.872	0.882	0.886	0.756	0.801	0.803
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B.

	Inverse Hyperbolic Sine Transformation						Weighted Regressions					
Dependent variable	Patent Count	Patent Entities	Citation	PC Top 10%	Generality	Originality	Patent Count	Patent Entities	Citation	PC Top 10%	Generality	Originality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High Tech×Enforce	0.3638***	0.3263***	0.3034***	0.2833***	0.3325***	0.3457***	0.3105***	0.2603***	0.2356**	0.2552***	0.2957***	0.2994***
	(4.79)	(4.68)	(3.39)	(3.58)	(3.84)	(4.13)	(3.81)	(3.66)	(2.55)	(3.10)	(3.18)	(3.30)
Observation	75,542	75,542	75,542	75,542	75,542	75,542	56,018	56,018	56,018	56,018	56,018	56,018
Adj. R-squared	0.883	0.891	0.888	0.757	0.801	0.812	0.889	0.900	0.904	0.771	0.815	0.825
Innovation Propensity×Enforce	0.4183***	0.3844***	0.2803***	0.3570***	0.4096***	0.4218***	0.3661***	0.3181***	0.2298**	0.3396***	0.3768***	0.3757***
	(4.37)	(4.19)	(2.77)	(3.75)	(4.01)	(4.22)	(3.79)	(3.56)	(2.30)	(3.49)	(3.55)	(3.59)
Observation	75,310	75,310	75,310	75,310	75,310	75,310	54,963	54,963	54,963	54,963	54,963	54,963
Adj. R-squared	0.886	0.895	0.890	0.766	0.810	0.819	0.893	0.904	0.907	0.781	0.824	0.833
Intangibility×Enforce	0.1530***	0.1364***	0.1107**	0.1661***	0.1441***	0.1551***	0.1435***	0.1221***	0.0856*	0.1600***	0.1460***	0.1526***
	(4.41)	(4.29)	(2.20)	(3.90)	(3.91)	(4.39)	(3.23)	(3.07)	(1.81)	(3.30)	(3.18)	(3.32)
Observation	78,662	78,662	78,662	78,662	78,662	78,662	57,269	57,269	57,269	57,269	57,269	57,269
Adj. R-squared	0.877	0.886	0.883	0.745	0.786	0.797	0.886	0.897	0.902	0.763	0.805	0.816
STD of MTB×Enforce	0.1131**	0.0873*	0.1475**	0.1436***	0.1738***	0.1657***	0.0703	0.0391	0.0798	0.1247***	0.1391***	0.1263***
	(2.28)	(1.84)	(2.29)	(3.94)	(4.21)	(4.13)	(1.57)	(0.94)	(1.31)	(3.54)	(3.44)	(3.26)
Observation	77,252	77,252	77,252	77,252	77,252	77,252	56,996	56,996	56,996	56,996	56,996	56,996
Adj. R-squared	0.878	0.887	0.885	0.750	0.795	0.805	0.886	0.897	0.902	0.765	0.809	0.818
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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 is evaluated as $Citation^c$ (left panel) and its annual change (right panel) for illustration purpose, netting out time fixed effects. $Citation^c$ is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in country *c*, and in year *t*, where *t* is the application year. 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) Level of Citation **(2) Change of Citation**

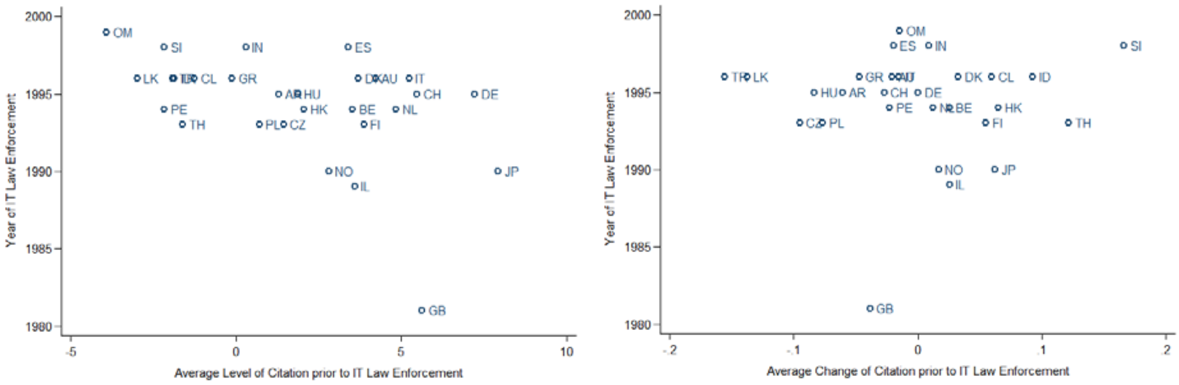

Figure 2 Innovation in Pre- vs. Post- Enforcement Period

The figures show the average annual country-level innovative activities in the pre- and post- enforcement period of insider trading laws. For illustrative purpose, innovation is evaluated as the total number of truncation-adjusted citations made to patent families in country *c*, year *t*, where *t* is the patent application year. Pre-enforcement period is defined as 5 years before the enforcement of insider trading laws, while post-enforcement period is defined as 5 years afterwards. We focus on the countries where insider trading laws were enforced between 1976 and 2006, and there are observations in both pre- and post- enforcement period. We first calculate the average number of forward citations to annually-filed patents over the [-5, -1] window and the [+1, +5] window respectively for each country. Then, for the pre- and post- enforcement period respectively, we calculate the cross-country average and plot the bar chart.

Citation

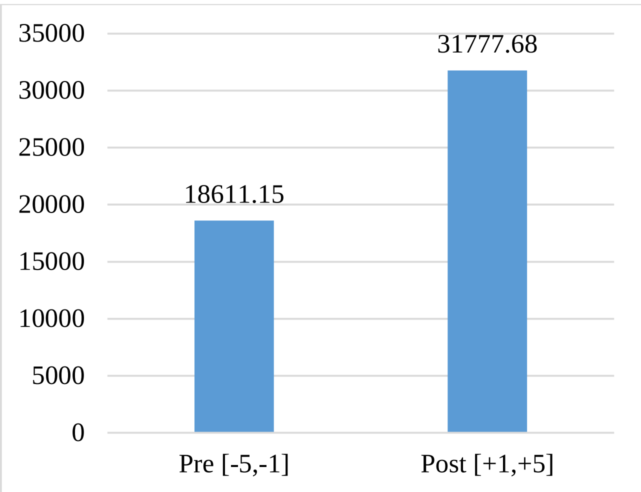

Figure 3 Dynamics of Insider Trading Law Enforcement and Innovation

The figures plot the dynamic impact of the enforcement of insider trading laws on country-level innovative activities. We focus on the countries where insider trading laws were enforced between 1976 and 2006. We use the following specification: $\text{Innovation}_{c,t} = \alpha_0 + \sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau}\text{Enforce}_{c,t,\tau} + \delta_c + \delta_t + \varepsilon_{c,t}$, where *Innovation* is evaluated as *Citation* ^{c} for illustration purpose. *Citation*^{c} is the natural logarithm of one plus the total number of truncation-adjusted citations to patent families in country *c*, and in year *t*, where *t* is the application year. Table 1 provides detailed definitions of the variables. A 15-year window spanning from 5 years before to 10 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 based on robust standard errors. The year of initial enforcement is excluded and serves as the benchmark year, and the plot is detrended and centered relative to the pre-enforcement average trend in citation.

Citation

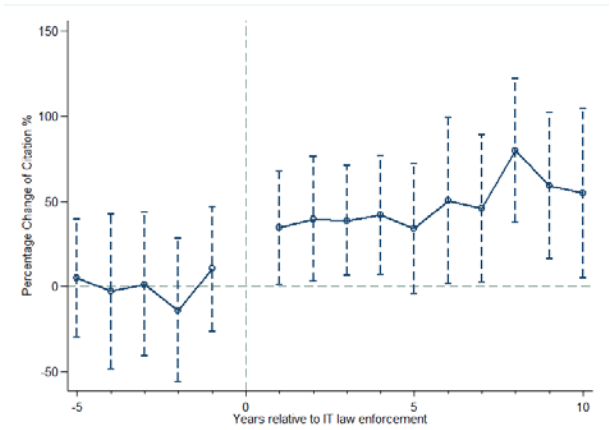

Figure 4 Other Market Conditions around Insider Trading Law Enforcement

The figures plot the dynamics of financial market development and trade activities around insider trading law enforcement. We focus on countries where insider trading laws were enforced between 1976 and 2006. We use the following specification: $\text{Covariate}_{c,t} = \alpha_0 + \sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau}\text{Enforce}_{c,t,\tau} + \delta_c + \delta_t + \varepsilon_{c,t}$, where *Covariate* takes the value of *Stock/GDP*, *Credit/GDP* and *Trade/GDP* respectively. A 15-year window spanning from 5 years before to 10 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 based on robust standard errors. The year of initial enforcement is excluded and serves as the benchmark year, and the plot is detrended and centered relative to the pre-enforcement average trend in the covariates.

(1) Stock/GDP **(2) Credit/GDP** **(3) Trade/GDP**

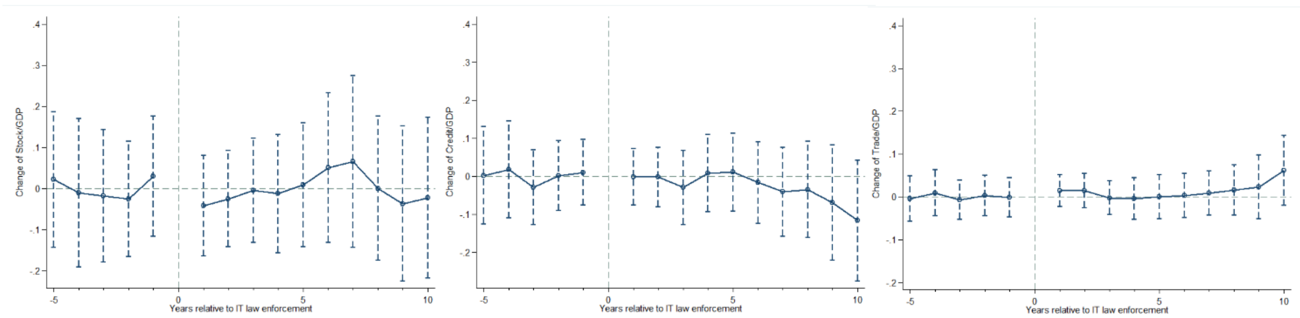

Figure 5 Dynamics of Insider Trading Laws and Innovation:
High-tech Intensive vs. Non-High-tech Intensive Industries

The figures plot the dynamic impact of the enforcement of insider trading laws on innovative activities in high-tech intensive and non-high-tech intensive industries. We use the following specification: $\text{Innovation}_{i,c,t} = \alpha_0 + \sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau,i=h} \text{High Tech}_i \times \text{Enforce}_{c,t,\tau} + \sum_{\tau=-10}^{\tau=+15} \alpha_{1,\tau,i=l} (1 - \text{High Tech}_i) \times \text{Enforce}_{c,t,\tau} + \lambda X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}$. *Innovation* is evaluated as *Citation* for illustrative purpose. *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. Control variables include *Enact*, *GDP*, *GDP per capita*, *Stock/GDP*, *Credit/GDP* and *Export to US*. A 15-year window spanning from 5 years before to 10 years after the year of initial enforcement is used in the estimation, with country, industry and year fixed effects included. The figures are based on estimated coefficients $\hat{\alpha}_{1,\tau,i=h}$ for high-tech intensive industries (blue line with circle) and $\hat{\alpha}_{1,\tau,i=l}$ for non-high-tech intensive industries (green line with triangle) respectively, both adjusted for the time-trend on $\hat{\alpha}_{1,\tau,i=l}$ w.r.t. the year of enforcement. The year of enforcement is the base year, on which the figures are centered.

Citation

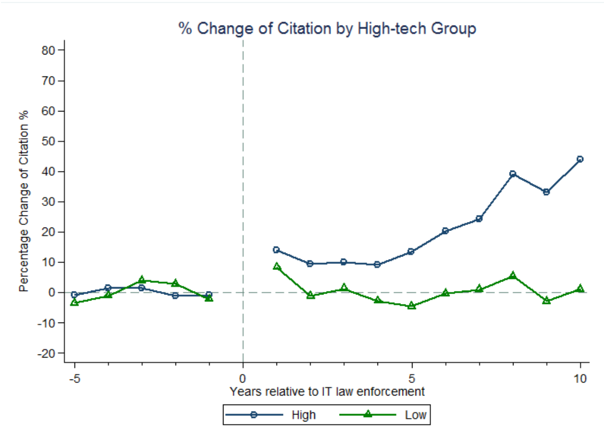

Figure 6 Equity Issuance in Pre- vs. Post- Enforcement Period

The figure shows the average annual country-level equity issuance activities in the pre- and post- enforcement period of insider trading laws. Pre-enforcement period is defined as 5 years before the enforcement of insider trading laws, while post-enforcement period is defined as 5 years afterwards. We include only countries where insider trading laws were enforced between 1976 and 2006, and there are observations in both pre- and post- enforcement period. We first calculate the average annual total equity issuance proceeds (mil$) over the [-5, -1] period and the [+1, +5] period respectively for each country, and then for the pre- and post- enforcement period respectively, we calculate the cross-country average and plot the bar chart.

Total Proceeds