Insider Trading and Innovation

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Abstract

We assess whether restrictions on insider trading accelerate or slow technological innovation. Using 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.

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, as shown by King and Levine (1993), Levine and Zervos (1998), Brown, Fazzari, and Petersen (2009), Brown, Martinsson, and Petersen (2012, 2017), and many others.[1] In turn, the law and finance literature finds that legal systems that protect minority shareholders from

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[1] For more on the linkages between financial development and innovation, see Beck, Levine, and Loayza (2000), Benfratello, Schiantarelli, Sembenelli (2008), Ayyagari, Demirgüç-Kunt, and Maksimovic (2011), Amore, Schneider, and Žaldokas (2013), Fang, Tian, and Tice (2014), Hsu, Tian, and Xu (2014), Laeven, Levine, Michalopoulos (2015), and Nanda and Rhodes-Kropf (2017).

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large shareholders foster better-functioning financial systems (see La Porta et al. 1997, 1998; Brown, Cookson, and Heimer 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 research and development (R&D) expenditures (Brown, Martinsson, and Petersen 2013; Brown and Martinsson 2017). However, while R&D expenditures directly measure corporate investments in R&D, 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 nonpublic 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 form of 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, Fishman, and Hagerty (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 (see, for example, Bushman, Piotroski, and Smith 2005; Fernandes and Ferreira 2009).[2] The resultant reduction in stock-price informativeness can impair investment in difficult-to-assess activities such as innovation (Holmstrom 1989) and impede the use of stock prices to improve managerial incentives (Manso 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 the staggered enactment and enforcement of insider-trading laws across countries and six measures of patenting activity and impact. We obtain information on the year when a country first enacts insider-trading laws and the year when it first prose-

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

[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 value for shareholders.

cutes a violator of those laws from Bhattacharya and Daouk (2002). We examine both enactment and enforcement because Bhattacharya and Daouk (2002) and others stress that only the 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 and 2006 from the European Patent Office's (EPO's) Worldwide Patent Statistical Database (PATSTAT).[4] We conduct our analyses at the industry level rather than the firm level because cross-country databases, such as Bureau van Dijk's 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 six proxies for technological innovation: the number of patents, to gauge the intensity of patenting activity; the number of forward citations to patents filed in this industry-country-year, to measure the impact of innovative activity; the number of patents in an industry-country-year that become top 10 patents, which are patents in the top 10 percent of the citation distribution of patents in the same technology class in a year, to measure high-impact inventions (Balsmeier, Fleming, and Manso 2017); the number of patenting entities, to assess the scope of innovative activities (Acharya and Subramanian 2009); the degree to which technology classes other than that of the patent cite the patent, to measure the generality of the invention; and the degree to which the patent cites innovations in other technology classes, to measure the originality of the invention (Hall, Jaffe, and Trajtenberg 2001).

We begin with preliminary analyses that simply differentiate by country and year and then shift to our core analyses that examine whether the relationships 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 an enforcement indicator that equals one after a country first enforces its insider-trading laws and zero otherwise and on an enactment indicator that 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. We control for gross domestic product (GDP) and GDP per capita to address concerns that the size of the economy and the level of economic development might shape 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 industries' exports to the United States.

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

[4] European Patent Office, PATSTAT (https://www.epo.org/searching-for-patents/business/patstat.html#tab-1).

patent-based measures of innovation. For example, the number of patents rises, on average, by 15 percent after a country first enforces its insider-trading laws, and citation counts rise by 29 percent. These results—in terms of both statistical significance and the estimated economic magnitudes—are robust to including or excluding time-varying country and industry controls.[5] On the other hand, we find no evidence that the enactment of insider-trading laws shapes innovation; rather, it is the enforcement of those laws that is tightly linked to innovation.

We were concerned that omitted variables might drive 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 several indictors of securities-market reforms and policies toward international capital flows; an array of indicators of bank regulatory and supervisory policies; and enactment of patent laws, measures of intellectual-property-rights protection, property-rights protection more generally, and the effectiveness of the legal system. Controlling for these factors does not alter the results.

We also show that there are no significant pretrends 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.[6] 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, which supports 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 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 ac-

[5] 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.

[6] It is also worth noting that in studies of the determinants of insider-trading laws, there is no indication that technological innovation or the desire to influence innovation affects the timing of when countries start enforcing their insider-trading laws. See, for example, Beny (2013).

curate valuations. Given that the United States is a highly innovative economy with well-developed securities markets and was 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 US industries, we evaluate whether innovative industries experience a bigger jump in innovation after a country starts enforcing its insider-trading laws.

Second, we differentiate industries by opacity. If insider trading discourages innovation by impeding market valuations, then the enforcement of insider-trading laws is likely to exert an especially large positive impact on innovation in industries with a high degree of informational asymmetries between insiders and potential outside investors. Put differently, there is less of a role for greater enforcement of insider-trading limits to influence innovation through the valuation channel if the prereform information gap is small. We use several proxies of opacity across industries, again using the United States 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 a violator of its insider-trading laws.

We find that all six of the patent-based measures of innovation increase 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 time-varying country factors that might be changing at the same time that a country first enforces its insider-trading laws and time-varying industry characteristics that might confound our ability to draw sharp inferences about the relationship between insider trading and innovation. We also control for the interaction of each of the industry-specific traits and the levels of economic and stock-market development to further mitigate omitted-variables concerns.

In terms of the estimated size of the impact, we find, for example, that, in industries that have above-median levels of natural innovativeness in the United States, citations to patents filed after a country begins to enforce its insider-trading laws increase about 32 percent more than in industries with below-median values. The same is true when splitting the sample by the natural opacity of industries. For example, in industries with above-median levels of intangible assets in the United States, citations to patents filed after a country begins to enforce its insider-trading laws increase 12 percent more than 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 initial public offerings and seasonal equity offerings increase much more in naturally innovative industries than in other industries after a country starts enforcing its insider-trading laws. In particular, the total proceeds from equity issuances increase 15–45 percent more in naturally innovative industries than 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 effectiveness of the legal system. All of the results hold. Similarly, time-invariant characteristics specific to an industry in 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 the omitted-variable bias test of Oster (forthcoming) and confirm our findings. Second, the results hold when examining different samples of countries or time periods. For example, the results are robust to restricting the sample to 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 1976–2006. The results also hold in industries with more patenting activities. Similarly, the results may be confounded by the formation of the European Union in the 1990s, as the timing of enforcing insider-trading laws 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 the engineering workforce and the fraction of innovative industries increase after a country enforces its insider-trading laws. 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. In the online appendix, we give more detailed summary statistics on each of the countries used in our analyses and provide the results from the robustness tests discussed below.

2.1. *Enforcement of Insider-Trading Laws*

Bhattacharya and Daouk (2002) compile data on the enforcement of insider-trading laws for 103 economies. They obtained these data by contacting stock exchanges and asking whether they had insider-trading laws; if yes, in what year they were first enacted; whether there had been prosecutions, successful or unsuccessful, under these laws; and, if yes, in what year the first prosecution took place. We start from the sample of countries that enacted insider-trading laws during our sample period, 1976–2006. We use the year in which a country first prosecutes a violator of its insider-trading laws rather than the date on which it enacts laws restricting insider trading because the existence of insider-trading laws without enforcement does not deter insider trading. Furthermore, following Bhattacharya and Daouk (2002) and others, we use the first time a country's authorities enforce insider-trading laws because the initial enforcement represents a shift of legal regime from a nonprosecuting to a prosecuting regime and signals a discrete jump in the probability of future prosecutions. This research suggests that the date the law is enforced—not the date it is enacted—signals the change of legal regime toward insider trading. We examine both below. In our sample, the 74 countries with complete data had insider-trading laws on their books by 2002, but only 29 countries enforced the laws before 2002. As a point of reference, the United States enacted laws prohibiting insider trading in 1934 and first enforced those laws in 1961, but the United States is not part of our sample.

We construct two variables for the enactment and enforcement of insider-trading laws. The term 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 zero otherwise. For years in which a country does not have insider-trading laws, Enforce equals zero; Enforce also equals zero in the year of the first enforcement, but our results are robust to setting it to one instead.

2.2. *Patents*

The EPO's PATSTAT provides data on more than 80 million patent applications filed in over 100 patent offices around the world. The database is updated biannually, and we use the 2015 spring release, which has data through the end of the fifth week of 2015. The database contains basic bibliographic information about patents, including the identity number of the application and granted patent, the date of the application, the date on which the patent is granted, the track record of patent citations, information about the patent's assignees (owners), and the technological subclass to which each patent belongs, according to the International Patent Classification (IPC) system.[7,8]

Critically, we focus on the original invention, since some inventions are patented in multiple patent offices. We use PATSTAT's identifier for a patent family, where a patent family includes all of the patents linked to a single invention. With this identifier, we determine the first time an invention is granted a patent and refer to it as the original patent. Following the patent literature, we date patents using the application year of the original patent rather than the year in which the patent is granted because the application year is closer to the date of the invention (Griliches, Pakes, and Hall 1987) and because using the application year avoids the problem of varying delays between the application and grant year (Hall, Jaffe, and Trajtenberg 2001). We also use the original patent to define the technological section and subclass(es) of the invention from its IPC symbol and record the country of residence of its primary assignee as the country of the invention.

We restrict the PATSTAT sample as follows. We include only patents filed with and eventually granted by the EPO or by one of the patent offices in the member countries of the Organisation for Economic Co-operation and Development (OECD) to ensure comparability across jurisdictions of intellectual property rights. We further restrict the sample to non-US countries because we use the United States as the benchmark economy when characterizing industry traits for all countries (Rajan and Zingales 1998). To further mitigate potential problems with using US industries as benchmarks, we include a country in the sample only 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) during our sample period because industries in these economies are presumably more comparable with those in the United States. This restriction excludes Zambia, Namibia, Botswana, and Mongolia. The results, however, are robust to in-

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

[8] The IPC symbols assigned to a patent can be inventive or noninventive. All patents have at least one inventive IPC symbol. We use only inventive IPC symbols for classifying a patent's technological section, class, and subclass. If the patent authority designates an inventive IPC symbol as secondary (L in the ipc_position of the Worldwide Patent Statistical Database [PATSTAT]), we remove that IPC symbol from further consideration. This leaves only inventive IPC symbols that the patent authority designates as primary (F in the ipc_position of PATSTAT) or that the patent authority does not designate as either primary or secondary—undesignated IPC symbols. In no case does a patent authority designate a patent as having two primary IPC symbols. In our data set, 19 percent of patents have multiple inventive IPC symbols (in which the patent authority designates the IPC symbol as primary or does not give it a designation), 6 percent have both a primary inventive IPC symbol and at least one undesignated IPC symbol, and 13 percent have no primary IPC symbol and multiple undesignated IPC symbols. In cases with multiple inventive IPC symbols, we first assign equal weight to each IPC subclass. That is, if a patent has two IPC subclasses, we count it as .5 in each subclass. From a patent's IPC subclasses, we choose the first IPC section according to the alphabetical ordering of the IPC sections.

cluding these countries or the United States in the regression analyses. Finally, since we use data from the United Nations Commodity Trade Statistics Database in our regression analyses, we exclude economies that it does not cover (Taiwan and Yugoslavia). Throughout the analyses, we follow the patent literature and focus on utility patents.[9] After implementing these restrictions and merging the patent data with the data on the enforcement of insider-trading laws, we have a sample of 74 economies for 1976–2006.[10]

When computing measures of innovation based on citations, we avoid double counting 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 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 they are patented.

Since we conduct our analyses at the industry-country-year level and merge data sources, we must reconcile the different industrial classifications used by PATSTAT and the other data sources and implement a criterion for including or excluding industry-country-year observations in which we find no evidence of patenting activity. With respect to industry categories, we convert the PATSTAT IPC symbols into two-digit Standard Industrial Classification (SIC) codes,[11] which yields 47 industries. 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 country-year, then we treat all subsequent years of the industry with no patent records as filing no patents and treat the years before the first recorded patent as missing.[12] 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 poor coverage of individual firms during our sample period. For example, the online platform Orbis provides data only since 2006, which is when our sample period ends.

[9] In addition to utility patents, PATSTAT includes two minor patent categories: utility models and design patents. As with the National Bureau of Economic Research Patent Database and consistent with US patent law, we include only utility patents.

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

[11] We first follow the mapping scheme provided by Lybbert and Zolas (2012) for converting IPC symbols into International Standard Industrial Classification (ISIC) codes. The World Intellectual Property Office provides the mapping scheme (Concordance Files [http://www.wipo.int/publications/en/details.jsp?id=3949&plang=EN]). We then convert the ISIC codes to Standard Industrial Classification (SIC) codes using the concordance scheme from United Nations Statistical Division, ISIC Rev. 3—US SIC 87, correspondences, English (https://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1).

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

2.3. Innovation Variables

We construct six measures of innovative activities for each industry-country-year. The variable Patent Count equals the natural logarithm of 1 plus the total number of eventually granted patent applications for industry *i* that are filed with the patent offices in one of the OECD countries and/or the EPO in year *t* by applicants from country *c*.[13] As emphasized above, we do everything at the level of the invention and patent family and then convert the PATSTAT IPC symbols to two-digit SIC codes. As we make the conversion from the IPC subclass to the SIC code 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.[14]

The variable Patent Entities equals the natural logarithm of 1 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 code 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 patents on future innovation (Acharya and Subramanian 2009; Hsu, Tian, and Xu 2014). Thus, we also use measures based on citations.

The variable Citation equals the natural logarithm of 1 plus the total number of citations to patent families in industry *i* in country *c* 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 count this as only one citation. Similarly, if two patents in the same patent family each cite an invention, we count it as only one citation. As emphasized above, we seek to measure citations by inventions of other inventions and not double count 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 PATSTAT, we adjust for truncation bias using the method developed by Hall, Jaffe, and Trajtenberg (2001, 2005).[15] Then we sum the citation counts over all patent families in each

[13] We follow the literature in using the natural logarithm of 1 plus the number of patents. See, for example, Atanassov (2013), Fang, Tian, and Tice (2014), Cornaggia et al. (2015), Gao and Zhang (2017), Brav et al. (forthcoming), and Mukherjee, Singh, and Žaldokas (2017).

[14] Each IPC symbol at the subclass level is matched to a spectrum of ISIC codes with a probability weight attached to each mapping route. We first construct the patent-count measure at the IPC subclass level. Then, for each pair of IPC-ISIC codes, we multiply the patent count by the probability weight. Next, for each ISIC code, we sum the weighted patent counts at the IPC symbols that are mapped to that ISIC code. Thus, we obtain the patent-count measure at the ISIC level. Finally, we obtain the patent-count measure at the SIC level using the concordance scheme.

[15] For patents granted in and before 1985 (for which at least 30 years of citations can be observed by the end of 2014), we use the citations recorded in PATSTAT. For patents granted after 1985, we implement the following four-step process to adjust for truncation bias. (1) Using each cohort of granted patents for which we have 30 years of citation data (patents granted in 1985 or earlier),

IPC subclass and convert this to the two-digit SIC code for each industry i in country c in year t.

The variable PC Top 10 Percent equals the natural logarithm of 1 plus the total number of highly cited patents, where we define a patent as highly cited if the number of forward citations it receives is in the top 10 percent of the citation distribution of patents filed in that technology class in the same year. We follow the approach in Balsmeier, Fleming, and Manso (2017) and use this measure to evaluate the success of innovation. We first categorize a patent on the basis of its position in the citation distribution for each IPC subclass and application year. After we identify the highly cited patents, we count the number in each IPC subclass and year and then convert it to the two-digit SIC code.

The variable Generality is a measure of the degree to which patents by each 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 1 minus the Herfindahl index of the IPC sections of patents citing it.[16] Thus, a patent's generality value equals 0 if the patent is cited only 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, that is, by sections other than the IPC section of the patent itself. Following Hsu, Tian, and Xu (2014), we then sum the generality values of all pat-

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 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 0. (2) We calculate the cumulative share of citations for section K from year 0 to year L. We refer to this cumulative share 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 patents granted before 1985, we compute the average cumulative share for each S_L^K over the 10 cohorts (1976–85) 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 $L = 28$ (that is, for 29 years, to the end of 2014). According to the calculations in step 3, this accounts for the share $\bar{S}_{L=28}^K$ of citations of a patent in section K that was granted in 1986 over a 30-year lifetime. We then multiply the citations of a patent in section K summed over 1986–2014 by the weighting factor $1/\bar{S}_{L=28}^K$ to compute the adjusted citations for a patent in section K and cohort 1986. As another example, consider a patent in section K and granted in 2006. We observe citations from $L = 0$ to $L = 8$ (that is, for 9 years, to the end of 2014). According to our calculations, these citations account for the share $\bar{S}_{L=8}^K$ of citations of a patent in section K that were granted in 2006 over a 30-year lifetime. In this example, then, we multiply the sum of citations over the period 2006–14 by the weighting factor $1/\bar{S}_{L=8}^K$ to compute the adjusted total citations for a patent in section K and cohort 2006.

[16] We follow the steps in Hall, Jaffe, and Trajtenberg (2001): For each patent i, we calculate c_i, the total number of patents citing patent i, and $c_{i,k}$, the number of patents in IPC section k that cite patent i, where k is one of the N_i sections to which the patents citing patent i belong (recall that there are eight IPC sections). 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. Next, for each patent i, we sum the squared percentage of citations from each IPC section k 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.

ents in 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 industry code (using the method describe above) and take the natural logarithm of 1 plus this summed generality value to obtain an overall generality measure at the industry-country-year level.

The variable Originality is a measure of the degree to which patents by each industry in a country cite patents in other technologies. Larger values of Originality indicate that patents in that industry build on innovations from a wider array of technologies. We construct Originality as follows. We first compute a patent's originality value as 1 minus the Herfindahl index of the IPC sections of patents that it cites. We then sum the originality values of all patents in each IPC subclass in each country and each year. Finally, we map this IPC-based indicator to SIC industries and take the natural logarithm of 1 plus the original value to obtain an overall originality measurement at the industry-country-year level.[17]

We also construct and use two variants of these measures: Patent Count*, Patent Entities*, Citation*, PC Top 10 Percent*, Generality*, and Originality* equal the values of the corresponding measures before the log transformation. 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 1 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 Percent^{c}, Generality^{c}, and Originality^{c} are defined analogously. We do not examine the efficiency with which R&D expenditures generate new patents because private firms often lack the requisite data for such analyses.

Appendix A and Table 1 provide detailed definitions and pooled summary statistics, respectively, for our variables. With respect to country-specific statistics, Patent Count* ranges from an average of .005 of a patent per industry-year in Tanzania to 468 patents per industry-year in Japan. The average number of truncation-adjusted citations for patents in an industry-year ranges from .02 in Tanzania to 9,620 in Japan. Table 1 further emphasizes the large dispersion in innovation across countries by pooling industry-country-years. On average, a country-industry has 22 eventually granted patents per year, while the standard deviation is as high as 148. Values for Citation* are also highly dispersed. In an average industry-country-year, the average value of Citation* is 320, with a standard deviation of 3,223.

[17] The terms Generality and Originality are based on Hall, Jaffe, and Trajtenberg (2001), but we use the eight IPC sections, while they 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 in each IPC subclass. There are about 600 subclasses in PATSTAT, which correspond closely in terms of granularity to the 400 categories (that is, three-digit classifications) in the US 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:

$$\text{Innovation}_{i,c,t} = \alpha_0 + \alpha_1 \text{Enforce}_{c,t} + \gamma \boldsymbol{X}'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{i,c,t}. \tag{1}$$

The variable $\text{Innovation}_{i,c,t}$ 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 Percent, Generality, and Originality. The regressor of interest is $\text{Enforce}_{c,t}$, which equals one in the years after a country begins to enforce 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 and contemporaneous events affecting all the observations in the same year. We use two-way clustering of errors at both the country and year levels.

The regression also includes time-varying country and industry characteristics ($\boldsymbol{X}$). We include Enact so that our analyses differentiate between putting insider-trading laws on the books and enforcing those laws. We include the natural logarithms of GDP and GDP per capita because the size of the economy and the level of economic development might influence 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, Baghai, and Subramanian 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 innovation and the enforcement of insider-trading laws. These country-level control variables are from the World Development Indicators (WDI) database and the Financial Development and Structure (FDS) database (Beck, Demirgüç-Kunt, and Levine 2010) via the World Bank. At the industry-country-time level, we control for the ratio of each industry's exports to the United States to the country's total exports to the United States in each year (Export to United States), since economic linkages with the United States might shape an industry's investment in innovation. The sample varies across specifications because of the availability of data for 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 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 ($\boldsymbol{X}$).

There are several challenges, however, that we must address to use 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; the rate

Table 1
Summary Statistics

	N	10th Percentile	Mean	Median	90th Percentile	SD
Industry level:						
Patent-based innovation measures:						
Patent Count*	83,200	0	22.3306	.2038	25.6827	148.1828
Patent Entities*	83,200	0	17.8754	.2654	27.3036	91.6897
Citation*	83,200	0	320.0123	.8196	191.0646	3,222.9220
PC Top 10 Percent*	83,200	0	1.8666	0	1.2031	17.5865
Generality*	83,200	0	3.7720	.0095	2.6566	31.2356
Originality*	83,200	0	4.0260	.0141	3.0598	32.6387
Patent Count	83,200	0	.9760	.1855	3.2840	1.4866
Patent Entities	83,200	0	1.0155	.2354	3.3430	1.4724
Citation	83,200	0	1.7482	.5986	5.2578	2.2649
PC Top 10 Percent	83,200	0	.2547	0	.7899	.6879
Generality	83,200	0	.3806	.0094	1.2965	.8694
Originality	83,200	0	.4074	.0140	1.4011	.8989
Industry characteristics:						
Export to United States	83,200	0	.0178	0	.0441	.0575
High Tech	79,881	0	.4903	0	1	.4999
Innovation Propensity	79,630	0	.4940	0	1	.5000
Intangibility	83,200	0	.4822	0	1	.4997
STD of MTB	81,699	0	.4973	0	1	.5000
Equity issuance:						
IPO Number	83,200	0	.0488	0	0	.2747
IPO Proceeds	83,200	0	.1466	0	0	.7961
Proceeds per IPO	83,200	0	.1182	0	0	.6462
SEO Number	83,200	0	.0578	0	0	.3098
SEO Proceeds	83,200	0	.1777	0	0	.9006
Proceeds per SEO	83,200	0	.1429	0	0	.7315
Total Issue Number	83,200	0	.0911	0	0	.3977
Total Proceeds	83,200	0	.2681	0	0	1.1052
Proceeds per Issue	83,200	0	.2096	0	0	.8712
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 Percent[c]	2,083	0	1.2958	0	4.3208	1.8964
Generality[c]	2,083	0	1.7458	.7282	4.9921	2.1359
Originality[c]	2,083	0	1.8150	.8280	5.2622	2.1745
Alternative innovation measures:						
ln(Engineering Workforce)	282	4.4096	5.9745	6.2246	7.2616	1.1278
Innovative Industry (Top 25 Percent)	2,083	0	.1864	.0769	.5957	.2340
Innovative Industry (Top 90 Percent)	2,083	0	.0742	0	.2340	.1389
Economic factors:						
Credit/GDP	1,939	.2033	.6721	.5436	1.3085	.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	.2480	.0612	.7337	.4550
Trade/GDP	1,943	.3349	.7673	.6611	1.3271	.4554

Table 1 (*Continued*)

Variable	N	10th Percentile	Mean	Median	90th Percentile	SD
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	.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	.5821	1	1	.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 and Legal Index	2,083	3.52	6.0703	6.18	8.37	1.8314
Patent Law	2,083	0	.4004	0	1	.4901
Legal and political factors:						
Common Law	2,083	0	.2876	0	1	.4527
Polity	1,884	−7	4.8747	9	10	6.8386
Fractionalization	1,832	.1376	.5803	.6348	.8210	.2433
Right	1,861	0	.3837	0	1	.4864
Central	1,861	0	.1134	0	1	.3171
Left	1,861	0	.3541	0	1	.4784

Note. Values are pooled summary statistics for the observations during 1976–2006. Statistics for industry-level variables are calculated for industry-country-year observations; statistics for country-level variables are calculated for country-year observations.

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 that 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 a 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 that the country starts enforcing insider-trading laws, 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 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 the level or rate of change in the patent-based measures predicts the timing of when countries start enforcing their insider-trading laws. Second, we find no pretrends 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 assessments of the degree to which omitted variables affect the analyses: we use a discontinuity design and test whether other factors, such as international trade or financial development, change in the same way that the patent-based indicators change after the enforcement of insider-trading laws; 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 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 theoretical perspectives on how protecting outside investors from corporate insiders will affect innovation. To do this, we augment the baseline specification with an interaction of Enforce and theoretically motivated industry traits, Industry, and with more granular fixed effects:

$$\text{Innovation}_{i,c,t} = \beta_0 + \beta_1 \text{Industry}_i \times \text{Enforce}_{c,t} + \lambda X'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t}. \quad (2)$$

The variable 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) 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 Industry × Enact, Industry × GDP per Capita, and Industry × Stock/GDP, as well as Export to United States 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 industry 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. If the enforcement of insider-trading laws promotes innovation by removing an impediment to the market's accurately evaluating innovations, then enforcement should have a particularly pronounced effect on innovation in industries most severely hampered by the impediment: naturally innovative industries. To measure which industries are naturally innovative—that is, industries that innovate more rapidly than other industries when national authorities enforce insider-trading laws—we follow Rajan and Zingales (1998) and use the United States as the benchmark country for defining the natural rate of innovation in each industry and construct and use two metrics based on the US data.

The first measure of the natural rate of innovation is High Tech, a dummy variable that designates whether an industry is technology intensive or not. Using Hsu, Tian, and Xu (2014), we first calculate high-tech intensiveness as the annual percentage of growth in R&D expenses for each publicly listed US firm in each year. We then use the cross-firm average in each two-digit SIC industry code 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 equals 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 hold when using continuous measures of the industry traits instead.

The second measure of 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 US firm in each year, we determine the number of patents it applied for in each US technological class defined in the current US class system. Second, for each US technological class in each year, we compute the average number of patents filed by a US firm. Third, we take the time-series average over the sample period in each technological class. Fourth, we map this to SIC industries using the mapping table in Hsu, Tian, and Xu (2014) and obtain each industry's US innovation propensity at the two-digit SIC level. The indicator variable Innovation Propensity equals one if the industry measure is above the sample median and zero otherwise.[18]

The second category of industry traits measures the natural opacity of each industry, that is, the difficulty of the market in 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 industries most hampered by informational asymmetries. To measure which industries are naturally opaque, we again use the United States as the benchmark country in constructing measures of opacity.

The first measure of whether an industry is naturally opaque is Intangibility, which measures the degree to which the industry has a comparatively large proportion of intangible assets. We use this measure under the assumption that intangible assets are more difficult for outsider investors to value than tangible assets, which is consistent with the empirical findings in Chan, Lakonishok, and Sougiannis (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

[18] The variable Innovation Propensity is computed after the United States first enforced its insider-trading laws, so this measure of natural innovativeness might capture some of the effects of enforcing insider-trading restrictions across US 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.

in each year, where PPE is a common measure of asset tangibility (see Baker and Wurgler 2002). We then calculate the average of the ratio of PPE to total assets across firms in the same industry-year and take the average over the sample period for each industry. We next compute 1 minus the PPE-to-total-assets ratio for each industry. Finally, we set Intangibility equal to one for industries in which 1 minus the PPE-to-total-assets ratio is greater than the median across industries and zero otherwise.

As a second measure of naturally opacity, we use the standardized dispersion of the market-to-book value of firms in US industries, where the standardization is determined relative to the average market-to-book equity ratio of publicly listed US 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 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 US publicly listed firms in each industry-year and take the average over time to measure market-to-book dispersion in each US industry. We then standardize the market-to-book dispersion by dividing it by the average market-to-book value of each industry. Accordingly, the variable STD of MTB equals one for observations above the cross-industry median and zero otherwise.

There might be concerns that the industry traits that focus on naturally innovative industries are empirically and conceptually related to those that focus on opacity because of the comparatively high costs of valuing innovative endeavors. However, High Tech and Intangibility both equal one in only 26 percent of industries, and the maximum correlation between either of the two natural innovativeness measures and the two natural opaqueness measures is less than .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) have above-median values of the intangibility measure (Intangibility equals one), but the chemical industry had an average growth rate in R&D expenditures of 43 percent per annum, whereas the corresponding growth rate in the transportation-services industry was only 3 percent during our sample period. In this case, the enforcement of insider-trading laws would enhance the valuation of both industries but 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, for industries with two-digit SIC codes of 35 (industrial and commercial machinery and computer equipment) and 32 (stone, clay, glass, and concrete products), both High Tech and Innovation Propensity equal one, 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 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 of the Strategies' Validity

In this section, we present four types of analyses that support the validity and value of our empirical strategy. To assess the assumption that the initial enforcement of insider-trading laws is not driven by preexisting innovative activities, we start by plotting the year that a country first enforced its insider-trading laws against the patent-based measures of innovation in the years before a country began to enforce its insider-trading laws and the rate of change of these patent-based measures before enforcement. We use the average values of pre-enforcement innovation measures net of year fixed effects for the plot. Figure 1 provides these two plots for Citation^c for countries that enforce their insider-trading laws at some point during 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 finding 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 prosecutes an insider-trading case in a given year conditional on the fact that no such prosecution had ever been initiated. We assume that the hazard rate follows a Weibull distribution and use the natural log of survival time, which is the expected time to the initial enforcement, as the dependent variable, where a longer time indicates a lower likelihood of being enforced. As the key explanatory variables, we use country-year measures of innovation. The term Patent Count^c is the natural logarithm of 1 plus the total number of eventually granted patent applications filed in year t by applicants from country c. The variable Patent Entities^c is the natural logarithm of 1 plus the total number of distinct entities in country c that apply for patents in year t. The variables Citation^c, PC Top 10 Percent^c, Generality^c, and Originality^c are defined similarly.

As shown in Table 2, preexisting patent-based measures of innovation do not predict the timing of the first enforcement action.[19] 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. We include legal origin, which indicates whether the country has a common-law legal heritage, because La Porta et al. (1998) and the subsequent literature emphasize how legal heritage can influence laws concerning financial contracting. We also include a measure of the extent of democracy in a coun-

[19] Table 2 provides the results for countries that enforced their insider-trading laws during the sample period and those that did not. The same results hold when including only countries that enforced their laws during the sample period.

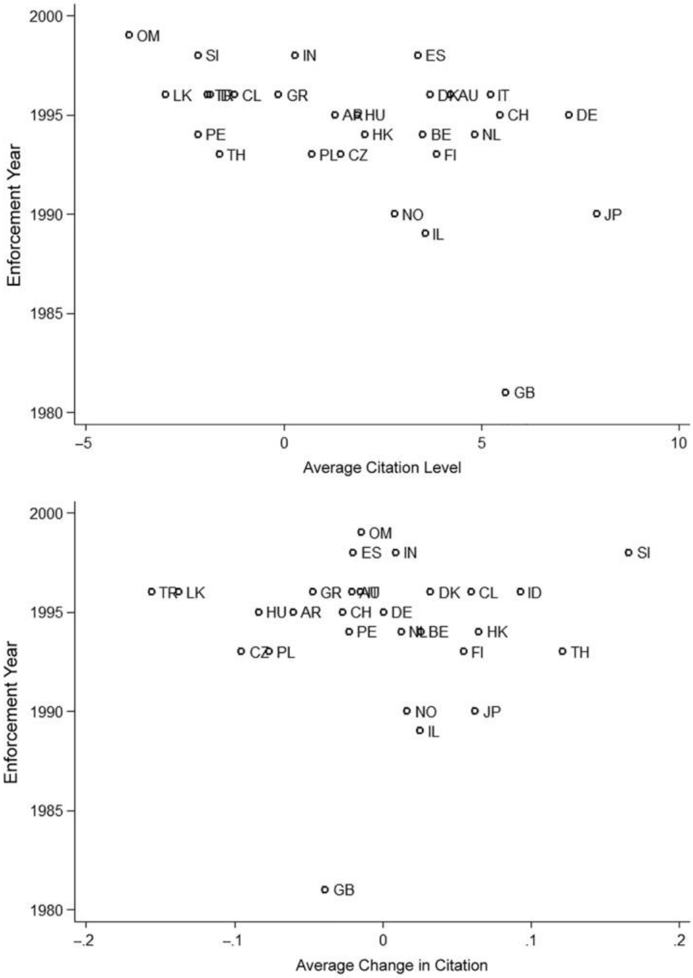

Figure 1. Timing of enforcement and preexisting innovation

try (Polity), with scores ranging from −10 (strongly autocratic) to 10 (strongly democratic), legislature fractionalization (Fractionalization, the probability that two randomly picked representatives in the legislature are from different parties), and indicators of political orientation of the largest party in the government (Right, Left, and Central) following Beny (2013).[20] 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

[20] The variable Polity is from the Polity IV database; Fractionalization and variables for political orientation (Right, Left, and Central) are from the Database of Political Institutions (Beck et al. 2001).

Table 2
Timing of Enforcement and Preexisting Innovation: Hazard-Model Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Patent Count[c]	−.1300					
	(−1.32)					
Patent Entities[c]		−.1154				
		(−1.01)				
Citation[c]			−.0392			
			(−.69)			
PC Top 10 Percent[c]				−.0440		
				(−.54)		
Generality[c]					−.0685	
					(−.79)	
Originality[c]						−.0121
						(−.13)
Common Law	−.1281	−.1177	−.0871	−.0887	−.0887	−.0992
	(−.58)	(−.53)	(−.40)	(−.42)	(−.42)	(−.45)
Polity	−.0008	−.0014	−.0072	−.0080	−.0070	−.0083
	(−.04)	(−.07)	(−.36)	(−.40)	(−.36)	(−.40)
Fractionalization	−.7041	−.7561	−.7343	−.7246	−.6976	−.7489
	(−1.36)	(−1.39)	(−1.36)	(−1.33)	(−1.31)	(−1.36)
Right	−.2406	−.2412	−.2426	−.2092	−.2062	−.2302
	(−1.39)	(−1.38)	(−1.36)	(−1.19)	(−1.20)	(−1.32)
Central	.3175	.3482	.3705	.3637	.3470	.3649
	(1.01)	(1.11)	(1.18)	(1.18)	(1.13)	(1.16)
GDP	−.1063	−.1418	−.2091*	−.2180*	−.1834+	−.2463*
	(−.89)	(−1.15)	(−2.53)	(−2.25)	(−1.69)	(−2.15)
GDP per Capita	.0361	.0231	−.0238	−.0374	−.0197	−.0517
	(.35)	(.20)	(−.24)	(−.45)	(−.23)	(−.56)
Stock/GDP	−.3430	−.3453	−.3029	−.3085	−.3114	−.3053
	(−1.38)	(−1.33)	(−1.16)	(−1.22)	(−1.26)	(−1.18)
Credit/GDP	.3964+	.3657	.3234	.3235	.3422	.2895
	(1.75)	(1.58)	(1.48)	(1.49)	(1.57)	(1.28)

Note. Values are the estimated effects of country-level patent-based measures of innovation before initial enforcement of insider-trading laws on the expected time to initial enforcement based on Weibull distribution of the hazard rate. The dependent variable is ln(Survival Time). Countries where insider-trading laws were not enforced during the sample period are treated as always at risk of enforcing the law; countries that enforced insider-trading laws during the sample period drop out of the sample after the law is enforced. Robust z-statistics based on standard errors clustered at the country level are in parentheses. $N = 1{,}306$.
$^{+}\,p < .10$.
$^{*}\,p < .05$.

across all six specifications. That is, we cannot reject the hypothesis that the patent-based measures of innovation do not predict when countries start enforcing their insider-trading laws.[21]

Third, we examine the dynamic relationship between innovation and when a country starts to enforce its insider-trading laws. In Figure 2, we present a simple

[21] 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.

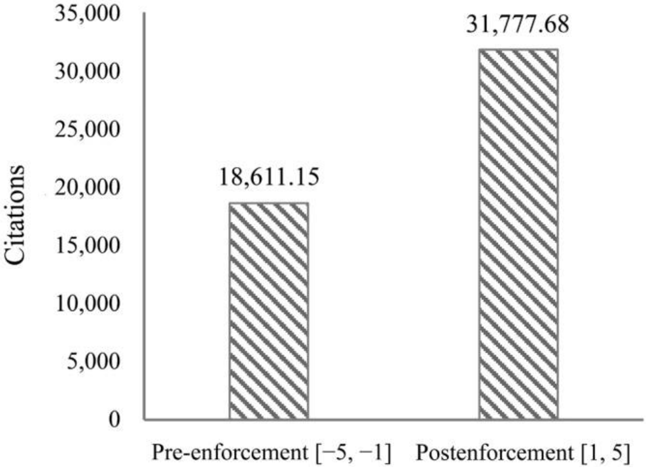

Figure 2. Innovation in pre-enforcement and postenforcement periods

pre- and postenforcement comparison of the patent-based measures of innovation. As in Figure 1, we use Citation^c for illustration and exclude countries in which insider-trading laws were not 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 postenforcement periods. The pre-enforcement (postenforcement) period is defined as the 5 years before (after) the enforcement of insider-trading laws. Then we calculate the average citation counts across countries for the two periods and present the values in Figure 2.

Noticeably, there is a substantial increase in citation counts of 71 percent after an average country begins to enforce its insider-trading laws. We find similarly sharp increases 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 causal connection if innovation was already 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 equation (3) for the same set of countries that enforced insider-trading laws during our sample period as used in Figures 1 and 2:

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

For illustrative purposes, we use Citation^c to proxy for Innovation$_{c,t}$. The dummy variable Enforce$_{c,t,\tau}$ equals one if the observation at time t is τ years away from the year of initial enforcement. If τ is greater than 0, then the dummy identifies the τth year after the initial enforcement of insider-trading laws; if τ is smaller than 0, it represents the τth year before initial enforcement. We include 15 dummies to examine the year-by-year effect on innovation from up to 5 years before

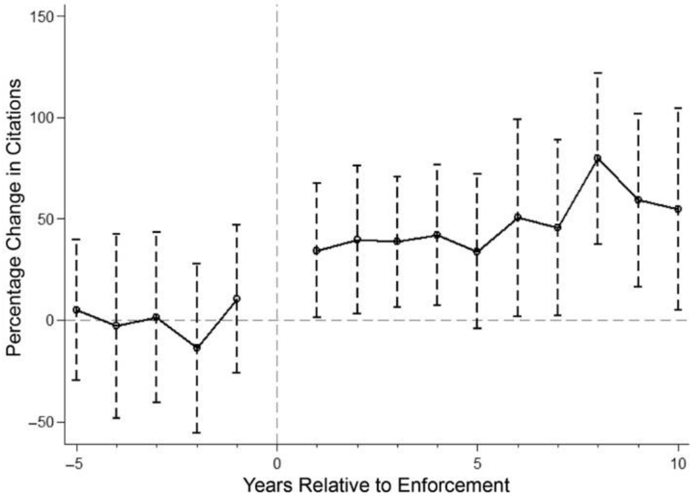

Figure 3. Dynamics of enforcement and innovation

the event to up to 10 years afterward. The year of initial enforcement is excluded from the regression and serves as the base year. 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 data. We plot the centered coefficient estimates in Figure 3. We include the 95 percent confidence intervals (dotted vertical lines) based on robust standard errors. Thus, the confidence intervals evaluate whether the estimated parameter is significantly different from the pre-enforcement mean adjusted for pre-enforcement trends.

Figure 3 demonstrates 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 shows a 34 percent increase in $Citation^c$ after 5 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 no trend in the patent-based measures of innovation prior to the year in which a country first enforces its insider-trading laws that carries into the postenforcement period. The overall pattern suggests that enforcing insider-trading laws has an immediate and enduring stimulative effect on innovation.

The fourth 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, Beny (2013) and other studies suggest that factors associated with international trade and overall financial development have shaped and have 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 the dependent variable. The term Stock/GDP measures the development of the domestic stock market; Credit/GDP measures the development of the domestic credit market; Trade/GDP gauges the intensity of international trade. As shown in Figure 4, neither the financial markets nor the international trade intensity changes in the same way that the patent-based indicators change after enforcement; indeed, Stock/GDP, Credit/GDP, and Trade/GDP do not change 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 assess the heterogeneous response of industries to enforcement.

4.1. Baseline Specification

Table 3 presents the regression results from 12 model specifications of baseline equation (1). Clustering the standard errors clustered at the country and year levels allows 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 begins to enforce its insider-trading laws. The coefficient on Enforce is positive and statistically significant in all 12 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 the regressions that include the broader set of control variables. The results indicate that the initial enforcement of insider-trading laws is associated with a 15 percent increase in the number of patents (patent intensity), a 12 percent increase in the number of patenting entities (scope of patenting activity), a 29 percent increase in citations (impact), an 11 percent increase in the number of highly cited patents (breakthrough innovation measured by PC Top 10 Percent), an 11 percent increase in the generality score (breadth of impact on other technologies), and a 17 percent increase in the originality score (breadth of other technologies cited).[22]

[22] It is worth noting two points with respect to the estimated coefficients. First, since only some patents will be commercialized, the rate of improvement in productive technologies may be slower than the rate of increase in these patent-based metrics. Second, since about two-thirds of the patents issued by public firms have an economic value greater than US$1 million (Kogan et al. 2017), our estimates suggest that the effect of insider-trading-law enforcement on value-enhancing technological development is about two-thirds of the impact on the patent-based metrics.

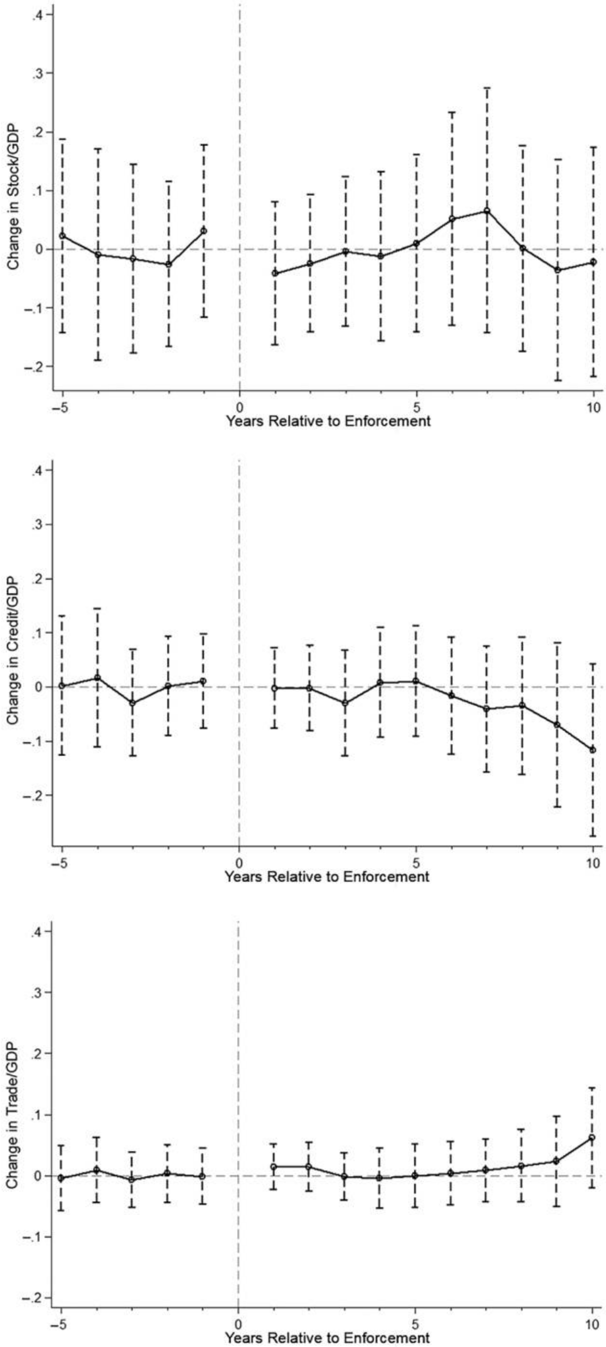

Figure 4. Other market conditions around enforcement

Table 3
Enforcement and Innovation: Baseline Results

	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality
Enforce	.2118*	.1661*	.3623**	.1338**	.1214**	.2235**
	(2.68)	(2.12)	(2.84)	(3.71)	(3.27)	(4.09)
Adjusted R^2	.839	.848	.847	.719	.762	.760
Enforce	.1547*	.1186+	.2948*	.1094**	.1059**	.1679**
	(2.44)	(1.94)	(2.59)	(3.50)	(3.43)	(3.58)
Control variables:						
Enact	.0098	.0109	−.0262	−.0022	.0034	−.0174
	(.25)	(.28)	(−.51)	(−.19)	(.25)	(−.94)
GDP	−.0011	.0525	−.1834	−.2136	−.1061	−.4966*
	(−.00)	(.21)	(−.37)	(−1.63)	(−.80)	(−2.66)
GDP per Capita	.4602*	.4593*	1.1689**	.3020*	.3436**	.6895**
	(2.29)	(2.40)	(2.95)	(2.71)	(3.20)	(4.28)
Stock/GDP	.1225*	.0970+	.2347*	.0791**	.0643+	.1097**
	(2.15)	(1.73)	(2.22)	(2.76)	(1.91)	(2.78)
Credit/GDP	.1155	.0995	.2213	.0236	.0210	.0501
	(1.58)	(1.34)	(1.60)	(.48)	(.46)	(.88)
Export to United States	1.2157**	1.0647**	1.4617**	.8264**	.9999**	.9820**
	(6.21)	(6.58)	(6.20)	(4.69)	(5.16)	(5.26)
Adjusted R^2	.853	.862	.861	.728	.771	.773

Note. Values are baseline effects of initial enforcement on innovation measured at the industry-country level using equation (1). The dependent variable is the natural logarithm of 1 plus the raw value of innovation measures at the industry-country-year level. All regressions include country, industry, and year fixed effects. Robust *t*-statistics based on standard errors clustered at the country-year level are in parentheses. $N = 83{,}200$ for regressions without control variables; $N = 76{,}561$ for regressions with control variables.

+ $p < .10$.
* $p < .05$.
** $p < .01$.

Consistent with earlier work emphasizing that the de facto change in the insider-trading regime occurs when the laws are enforced, not when they are enacted, we find that Enact does not enter significantly. 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, Wang, and Wu (2016), we also evaluate the explanatory power of the fixed effects to provide additional evidence for our empirical design. In unreported results, we find that the adjusted R^2-value of 14.8 percent in the Patent Count model with only Enforce and year dummies as the regressors increases to 57.5 percent when including the full set of country and industry characteristics and to 85.3 percent when also including country and industry fixed effects. The increase in the adjusted R^2-value suggests that the addition of time-varying country and industry characteristics absorbs 42.7 percent of the additional variation in the rate of innovation, and the addition of country and industry fixed effects leads to a further improvement of 27.8 percent of the variation explained over and above the time-varying country and industry characteristics. Moreover, an F-test shows that the set of control variables, country fixed effects, and industry fixed effects are each jointly significant at the 1 percent level in the full model in Table 3. 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 4. We add the following 16 terms to the regressions in Table 3: Credit Control, which is an index of the restrictiveness of reserve requirements, existence of mandatory credit-allocation requirements, and credit ceilings, with larger values for fewer restrictions; Interest-Rate Control, which measures the inverse of the extent to which the authorities control interest rates; Entry Barriers, which measures the ease of foreign bank entry and the extent of competition in the domestic banking sector (such as restrictions on branching); Bank Supervision, which measures the degree of supervision over the banking sector; Bank Privatization, which measures the presence of state-owned banks; Capital Control, which measures restrictions on international capital flows, with larger values associated with fewer restrictions; Securities Market, which measures the level of development of securities markets and restrictions on foreign equity ownership; Financial Reform Index, which is the sum of the previous seven variables; Liberal Capital Markets, which equals one after a country officially liberalizes its capital market and zero otherwise (and indicates whether the country implemented formal regulatory changes that permit foreign investors 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); IPR Protection, which measures the strength of intellectual-property-rights protection in particular; PR Protection, which gauges the strength of property-rights protection in general; Legal Integrity, which evaluates the extent of impartiality of the legal system and general observance of the law in a country; Contract Enforcement, which measures the effectiveness of contract enforcement; PR and Legal Index, which measures the overall strength of legal and property-rights protection and is defined as the average of nine subindexes, including IPR Protection, PR Protection, Legal Integrity, and Contract Enforcement; and Patent Law, which equals one for the years after a country enacts its first patent law and zero before. Finally, we include Financial Reform Index, PR and Legal Index, and Patent Law together to control for aggregate policies toward financial liberalization, property-rights protection, and the legal environment. Appendix A provides detailed definitions and data sources for these variables.

The results are robust to controlling for these indicators of policy reforms. Table 4 summarizes the results from 96 regressions, as we examine the 16 policy-reform indicators for the six patent-based indicators of innovation. As shown, even when controlling for the policy reforms, separately or together, Enforce enters each of the regressions significantly. Indeed, when controlling for the policy indicators, the estimated coefficient varies little from the estimates reported in

Table 4

Enforcement and Innovation: Controlling for Policy Changes

	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality
Credit Control	.1519*	.1165+	.3113**	.0939**	.1005**	.1255*
	(2.43)	(1.96)	(3.03)	(3.01)	(3.29)	(2.63)
Interest-Rate Control	.1531*	.1172+	.3110**	.0942**	.1008**	.1255*
	(2.45)	(1.97)	(3.03)	(3.05)	(3.32)	(2.67)
Entry Barriers	.1532*	.1174*	.3114**	.0943**	.1008**	.1261*
	(2.62)	(2.10)	(3.16)	(3.10)	(3.36)	(2.67)
Bank Supervision	.1532*	.1173+	.3143**	.0938**	.1005**	.1252*
	(2.43)	(1.95)	(3.08)	(3.05)	(3.32)	(2.63)
Bank Privatization	.1471*	.1117+	.3071**	.0929**	.0991**	.1243*
	(2.52)	(2.01)	(3.06)	(3.05)	(3.38)	(2.62)
Capital Control	.1478*	.1125+	.3169**	.0920**	.0993**	.1238*
	(2.33)	(1.84)	(3.03)	(2.98)	(3.24)	(2.59)
Securities Market	.1526*	.1160+	.3038**	.0957**	.1005**	.1282*
	(2.50)	(2.00)	(3.09)	(3.09)	(3.33)	(2.66)
Financial Reform Index	.1490*	.1135+	.3108**	.0927**	.0996**	.1234*
	(2.44)	(1.94)	(3.01)	(3.07)	(3.30)	(2.65)
Liberal Capital Markets	.1961**	.1606*	.3252*	.1171**	.1220**	.1773**
	(3.21)	(2.75)	(2.60)	(3.55)	(3.76)	(3.71)
IPR Protection	.1843**	.1470*	.3766**	.1132**	.1184**	.1663**
	(2.90)	(2.39)	(3.42)	(3.77)	(3.78)	(3.56)
PR Protection	.1576*	.1216+	.2976*	.1098**	.1073**	.1696**
	(2.50)	(2.01)	(2.63)	(3.56)	(3.54)	(3.70)
Legal Integrity	.1634*	.1272*	.3125**	.1113**	.1088**	.1704**
	(2.60)	(2.10)	(2.86)	(3.55)	(3.54)	(3.67)
Contract Enforcement	.1538*	.1186+	.2914*	.1082**	.1058**	.1662**
	(2.42)	(1.94)	(2.59)	(3.48)	(3.41)	(3.58)
PR and Legal Index	.1563*	.1201+	.2919*	.1095**	.1068**	.1680**
	(2.47)	(1.97)	(2.52)	(3.51)	(3.48)	(3.59)
Patent Law	.1549*	.1188+	.2957*	.1092**	.1060**	.1675**
	(2.43)	(1.94)	(2.58)	(3.52)	(3.43)	(3.61)
Financial Reform Index, PR and Legal Index, and Patent Law	.1534*	.1185*	.3114**	.0937**	.1001**	.1266*
	(2.66)	(2.14)	(2.95)	(3.09)	(3.34)	(2.74)

Note. Values are coefficients on Enforce using equation (1) and controlling for policy changes related to financial liberalization, property-rights protection, and general legal enforcement. All regressions include time-varying controls (Enact, GDP, GDP per Capita, Stock/GDP, Credit/GDP, and Export to United States) and country, industry, and year fixed effects. Robust *t*-statistics based on standard errors clustered at the country-year level are in parentheses.

$^{+}$ $p < .10$.
* $p < .05$.
** $p < .01$.

Table 3. These results help mitigate concerns that 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 depend 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, and general measures of property-rights protection and contract enforcement.[23]

A related concern is that increases in patent count may result from higher rates of patenting of existing technologies rather than new inventions. Thus, we analyze two alternative measures of innovation at the country level. The first measure is the size of the engineering workforce in R&D, Engineering Workforce, which equals the number of technicians in R&D per 1 million people. We obtain the data from the WDI database of the World Bank. As the data coverage starts in 1996, we restrict the sample period of the regressions to 1996–2006. We use ln(Engineering Workforce) as the dependent variable considering skewness in the measure (the 10th and 90th percentiles are 82 and 1,425, respectively), but the results are robust to using Engineering Workforce as the dependent variable. We present the results in Table 5. The full sample includes countries where insider-trading laws were enacted between 1976 and 2006. We also present results for a sample that excludes countries where insider-trading laws were enforced by 1996, as Enforce equals one for those countries during the period 1996–2006. Our results are robust to using both samples. For the smaller sample, the size of the engineering workforce increases by 34 percent 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.[24] Second, if the average number of patents per firm in an industry-country-year is in the top 25 percent (across the full sample of industry-country-year observations), we categorize the industry as innovative. We then compute the fraction of innovative industries in each country-year and call this Innovative Industry (Top 25 Percent). We follow a similar procedure to compute Innovative Industry (Top 10 Percent) for industry-country-year observations in the top 10 percent of

[23] Brown and Martinsson (2017) examine the relationship between corporate transparency and both research and development (R&D) expenditures and patent counts. 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. 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 and the other indictors of innovation discussed below, we assess whether the impact of the enforcement of insider-trading laws on patent-based measures of innovation and the degree to which firms raise funds through equity issuances varies across industries in a theoretically predictable manner. 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.

[24] 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 its online platform.

Table 5

Enforcement and Alternative Country-Level Measures of Innovation

	ln(Engineering Workforce)		Innovative Industry (Top 25 Percent)	Innovative Industry (Top 10 Percent)
	(1)	(2)	(3)	(4)
Enforce	.2460**	.3422**	.0291**	.0230**
	(2.63)	(3.20)	(4.62)	(6.52)
N	275	155	1,867	1,867
Adjusted R^2	.963	.963	.943	.951
Sample	Full	Enforced by 1996	Full	Full

Note. Results are from the specification $\text{Innovation}_{c,t} = \alpha_0 + \alpha_1\text{Enforce}_{c,t} + \gamma\boldsymbol{X}'_{c,t} + \delta_c + \delta_t + \varepsilon_{c,t}$. All regressions include time-varying controls (Enact, GDP, GDP per Capita, Stock/GDP, Credit/GDP, and Trade/GDP) and country and year fixed effects. Robust *t*-statistics based on standard errors clustered at the country-year level are in parentheses.

** $p < .01$.

the full sample. We then use these country-year observations as dependent variables 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 in Table 5 show that enforcement is associated with a statistically significant and material increase in the proportion of innovative industries. The value for Innovative Industry (Top 25 Percent) increases by 3 percentage points after a country enforces insider-trading laws, which is 16 percent of the sample average.

We conducted several additional robustness tests. First, to reduce concerns about omitted variables, we controlled for country-industry fixed effects and year fixed effects and implemented the Oster (forthcoming) test for omitted-variable bias. The results hold when adding these additional controls, and the Oster test suggests that our findings are not influenced by omitted variables. Second, to assess the sensitivity of the findings to different assumptions about the errors, we clustered the standard errors at the country level, the industry-year level, the country and industry level, and the country-industry-year level. The results are robust to these different clustering assumptions. Third, we verified that the results hold when using a country-level sample. Fourth, we were concerned that participation in the European Union could stimulate innovation, which would confound our interpretation of the regression results. The results, however, hold when excluding EU member countries that first enforced their insider-trading laws in the 1990s. Finally, to address the concern that multinational firms may shift innovation across borders without much real effect on the domestic economy, we restricted the sample to industries with little multinational presence in a country and find that the results hold.

4.2. *Heterogeneous Responses by Industry*

In this section, 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 theories of 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's 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 industries most constrained by the absence of enforcement, such as 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 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 Natural Innovativeness

Based on equation (2), Table 6 uses the interaction terms High Tech × Enforce and Innovation Propensity × Enforce to 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. The patent-based measures of innovation rise much more in high-tech industries after a country begins to enforce its insider-trading laws. For example, the number of patents increases approximately by 35 percent 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 during the sample period is greater than the median. The large difference between high-tech and other industries holds for the other patent-based measures. After a country begins to enforce its insider-trading laws, high-tech industries experience larger increases in the measures Patenting Entities, Citations, PC Top 10 Percent, Generality, and Originality than other industries. Because we control 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 laws unless those changes also differentially affect industries in precisely this manner. Similarly, because we control for industry-year effects, the results are not due to international increases in the rates of innovation in high-tech industries.

Table 6 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 US industry is greater than the median. The interaction term Innovation Propensity × Enforce enters each of the regressions positively and significantly at the 1 percent level. The estimated effects are large. For example, among indus-

Table 6

Enforcement and Innovation: Cross-Industry Heterogeneous Reponses

	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality
High Tech × Enforce	.3491**	.3158**	.3245**	.2397**	.2900**	.3039**
	(4.92)	(4.95)	(3.72)	(3.48)	(3.73)	(4.01)
Adjusted R^2	.875	.884	.888	.751	.794	.805
Innovation Propensity × Enforce	.4122**	.3833**	.3107**	.3004**	.3581**	.3728**
	(4.69)	(4.61)	(3.21)	(3.59)	(3.89)	(4.11)
Adjusted R^2	.880	.889	.890	.760	.803	.812
Intangibility × Enforce	.1579**	.1425**	.1197*	.1455**	.1360**	.1468**
	(4.77)	(4.73)	(2.70)	(3.82)	(3.97)	(4.39)
Adjusted R^2	.869	.878	.882	.740	.779	.790
STD of MTB × Enforce	.1265**	.1028*	.1551*	.1260**	.1589**	.1553**
	(2.98)	(2.55)	(2.59)	(3.94)	(4.31)	(4.36)
Adjusted R^2	.870	.880	.884	.745	.788	.798

Note. Values are results from equation (2). The dependent variable is the natural logarithm of 1 plus the raw value of innovation measures. All regressions include time-varying controls (interactions of the innovation measure with Enact, GDP per Capita, Stock/GDP, and Export to United States) and country-year and industry-year fixed effects. Robust *t*-statistics based on standard errors clustered at the country-year level are in parentheses. $N = 75{,}542$ for High Tech; $N = 75{,}310$ for Innovation Propensity; $N = 78{,}662$ for Intangibility; $N = 77{,}252$ for STD of MTB.

* $p < .05$.

** $p < .01$.

tries for which Innovation Propensity equals one, the number of patents by the average industry rises approximately by 41 percent more than that by an average industry for which Innovation Propensity equals 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. We extend the dynamic regression in equation (3) to the industry level and modify it by interacting a series of time dummies with High Tech equal to one or zero. We then estimate the following regression:

$$\begin{aligned} \text{Innovation}_{i,c,t} = \alpha_0 &+ \sum_{\tau=-10}^{\tau=15} \alpha_{1,\tau,i=h} (\text{High Tech}_i) \times \text{Enforce}_{c,t,\tau} \\ &+ \sum_{\tau=-10}^{\tau=15} \alpha_{1,\tau,i=l} (1 - \text{High Tech}_i) \times \text{Enforce}_{c,t,\tau} \\ &+ \lambda X'_{i,c,t} + \delta_c + \delta_i + \delta_t + \varepsilon_{c,t}, \quad \text{where } \tau \neq 0. \end{aligned} \tag{4}$$

Control variables include Enact, GDP, GDP per Capita, Stock/GDP, Credit/GDP, and Export to United States. A 15-year window spanning from 5 years before to 10 years after the year of initial enforcement is used. The year of enforcement is the base year; thus, it is excluded from the regression. The estimated coefficients

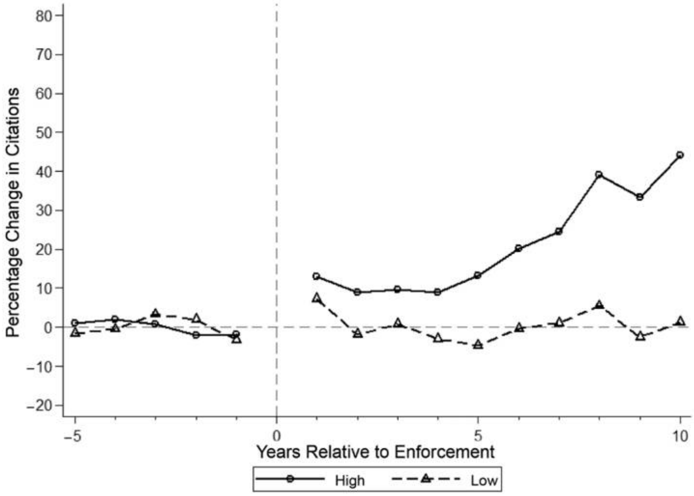

Figure 5. Dynamics of insider-trading laws and innovation: high- versus low-tech industries

$\hat{\alpha}_{1,\tau,i=h}$ 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 Figure 3, we center the data by subtracting the group-specific pre-enforcement mean from the trend-adjusted coefficients.

As shown in Figure 5 for 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, which indicates parallel trends. After a 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 Natural Opacity

We next assess whether industries that are naturally opaque experience a bigger increase in innovative activity after a country begins to enforce 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 enforcement will have a particularly positive impact on valuations—and hence innovation—in industries in which informational asymmetries most severely impede 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 6, we find that more opaque industries—as proxied by Intangibility equal to one—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. The interaction term Intangibility × Enforce enters positively and significantly at the 5 percent level in the Patent Count, Patent Entities, Citation, PC Top 10 Percent, Generality, and Originality regressions. Furthermore, the effect is large. Across the patent-based measures of innovation, innovation increases by 12–16 percent more in opaque industries than in other industries after a country starts enforcing its insider-trading laws.

We use the dummy variable defined on the standard deviation of the market-to-book ratio, STD of MTB, as an alternative proxy for informational opacity. 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 begins to enforce its insider-trading laws than other industries. In particular, STD of MTB × Enforce enters positively and significantly in all regressions in Table 6. These findings are consistent with theories emphasizing that the enforcement of insider-trading laws reduces the disincentives to expend resources on valuing projects and that the reduction of these disincentives has an especially big impact on naturally innovative and opaque industries.

4.2.3. Robustness Tests

To address the concern that industry-country-specific policies may drive the patterns of innovation and the timing of the enforcement of insider-trading laws, we examine the sensitivity of the results in Table 6 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 4. We confirm that all of the results in Table 6 hold when adding these interaction terms, and we present the results based on High Tech in Table 7. Consistent with the view that enforcing insider-trading laws improves valuations and these improvements have a particularly large effect on naturally innovative and opaque industries, we find that High Tech × Enforce, Innovation Propensity × Enforce, Intangibility × Enforce, and STD of MTB × Enforce continue to enter the innovation regressions positively and significantly, with point estimates similar to those reported in Table 6. This evidence eases concerns that the cross-industry patterns of innovation and the enforcement of insider-trading laws simply reflect these

Table 7

Enforcement and Innovation: Controlling for Policy Effects across Industries

	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality
Credit Control × Enforce	.2339**	.1951**	.2309*	.1736*	.1995*	.2041*
	(3.39)	(3.08)	(2.55)	(2.69)	(2.68)	(2.75)
Interest-Rate Control × Enforce	.2346**	.1956**	.2282*	.1735*	.1985*	.2035*
	(3.35)	(3.06)	(2.51)	(2.60)	(2.58)	(2.67)
Entry Barriers × Enforce	.2272**	.1886**	.2190*	.1665*	.1901*	.1953*
	(3.34)	(3.05)	(2.55)	(2.58)	(2.55)	(2.66)
Bank Supervision × Enforce	.2278**	.1869**	.2228*	.1734*	.1950*	.1990*
	(3.10)	(2.86)	(2.39)	(2.49)	(2.45)	(2.52)
Bank Privatization × Enforce	.2336**	.1942**	.2378*	.1696*	.1964*	.2021*
	(3.31)	(3.05)	(2.56)	(2.47)	(2.49)	(2.62)
Capital Control × Enforce	.2339**	.1951**	.2286*	.1730*	.1976*	.2030*
	(3.34)	(3.07)	(2.51)	(2.60)	(2.58)	(2.68)
Securities Market × Enforce	.2257**	.1876**	.2201*	.1678*	.1905*	.1961*
	(3.32)	(3.06)	(2.47)	(2.54)	(2.51)	(2.61)
Financial Reform Index × Enforce	.2349**	.1957**	.2297*	.1731*	.1992*	.2042*
	(3.37)	(3.06)	(2.52)	(2.62)	(2.61)	(2.70)
Liberal Capital Markets × Enforce	.3102**	.2758**	.2981**	.2893**	.3411**	.3454**
	(3.78)	(3.82)	(2.86)	(3.75)	(3.95)	(4.03)
IPR Protection × Enforce	.2746**	.2418**	.2557**	.2067**	.2375**	.2487**
	(4.41)	(4.23)	(3.02)	(3.33)	(3.46)	(3.69)
PR Protection	.3278**	.2955**	.2978**	.2230**	.2670**	.2808**
	(4.69)	(4.77)	(3.65)	(3.36)	(3.61)	(3.91)
Legal Integrity × Enforce	.3406**	.3076**	.3154**	.2372**	.2860**	.2996**
	(4.82)	(4.85)	(3.63)	(3.46)	(3.70)	(3.97)
Contract Enforcement × Enforce	.3531**	.3190**	.3283**	.2405**	.2916**	.3057**
	(5.02)	(5.11)	(3.85)	(3.45)	(3.73)	(4.01)
PR and Legal Index × Enforce	.3491**	.3158**	.3245**	.2397**	.2900**	.3039**
	(5.02)	(5.09)	(3.80)	(3.51)	(3.79)	(4.08)
Patent Law × Enforce	.3108**	.2796**	.2661**	.2080**	.2491**	.2656**
	(4.50)	(4.41)	(3.19)	(3.30)	(3.48)	(3.75)
Financial Reform × Enforce, PR and Legal Index × Enforce, and Patent Law × Enforce	.1972**	.1594*	.1645*	.1405*	.1579*	.1663*
	(3.07)	(2.70)	(2.07)	(2.33)	(2.28)	(2.45)

Note. Values are industry-level partitioned regression results of equation (2) for High Tech × Enforce, controlling for the interaction between industry categorization and policy changes. All regressions include time-varying controls (interactions of High Tech with Enact, GDP per Capita, Stock/GDP, and Export to United States) and country-year and industry-year fixed effects. Robust *t*-statistics based on standard errors clustered at the country-year level are in parentheses.

* $p < .05$.

** $p < .01$.

other policy changes. Again, we find that Industry × Enact does not enter the regressions significantly in any industry-partitioned analysis, which confirms that effective restrictions on insider trading start from enforcement rather than enactment of insider-trading laws.

These industry-level analyses are robust to several additional tests. First, for the regressions in Table 6, where industries are categorized by indicator variables, we performed a robustness check using continuous measures of the industry traits. The results hold. Second, we tested 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. To conduct this test, we constructed three industry-level measures of the latent probabilities of insider trading based on US industries. We find 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. Third, the results are robust to restricting the sample to countries that enforced their insider-trading laws during our sample period.

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 them. 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 enforcement 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 in-

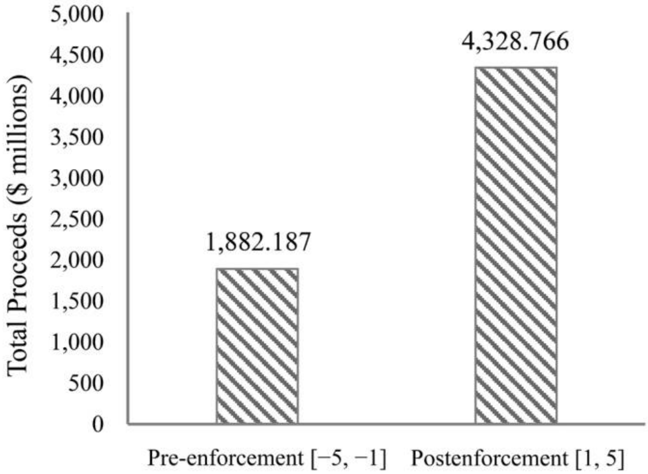

Figure 6. Equity issuance in pre- and postenforcement periods

novative 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 1 plus the number of IPOs (IPO Number), the natural logarithm of 1 plus the proceeds of those IPOs in US dollars (IPO Proceeds), and the natural logarithm of 1 plus the average amount raised (in US dollars) per IPO (Proceeds per IPO). We calculate similar measures for SEOs (SEO Number, SEO Proceeds, and Proceeds per SEO) and for totals 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 postenforcement 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-enforcement (postenforcement) period as the 5 years before (after) the enforcement of insider-trading laws, similar to Figure 2. 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 estimates, we use the following equation:

$$\begin{aligned}\text{Equity Issuance}_{i,c,t} = \beta_0 + \beta_1 \text{Industry}_i \times \text{Enforce}_{c,t} \\ + \lambda \boldsymbol{X}'_{i,c,t} + \delta_{c,t} + \delta_{i,t} + \varepsilon_{i,c,t},\end{aligned} \tag{5}$$

where Equity $\text{Issuance}_{i,c,t}$ is one of the nine measures of equity issuances and Industry_i is High Tech, Innovation Propensity, Intangibility, or STD of MTB in Table 8. Table 8 provides the regression results partitioned by the natural rate of innovation from nine regressions in which the interaction term is High Tech $\times$ Enforce or Innovation Propensity $\times$ Enforce.

As shown in Table 8, equity issuances increase substantially more in naturally

Table 8

Enforcement and Equity Issuance: Cross-Industry Heterogeneous Reponses

	IPO Number	IPO Proceeds	Proceeds per IPO	SEO Number	SEO Proceeds	Proceeds per SEO	Total Issue Number	Total Proceeds	Proceeds per Issue
High Tech × Enforce	.0580**	.1288*	.0847*	.0686**	.1328*	.0789+	.0895**	.1527*	.0782+
	(2.90)	(2.33)	(2.12)	(2.95)	(2.54)	(2.03)	(3.12)	(2.37)	(1.72)
Adjusted R^2	.382	.316	.287	.421	.322	.262	.473	.387	.324
Innovation Propensity × Enforce	.1027**	.2649**	.1867**	.1367**	.3707**	.2631**	.1783**	.4482**	.2998**
	(3.13)	(2.91)	(2.94)	(3.61)	(3.93)	(3.96)	(3.75)	(3.85)	(3.83)
Adjusted R^2	.389	.323	.292	.432	.335	.274	.484	.400	.333
Intangibility × Enforce	.0603*	.1386*	.0889*	.0553*	.1308*	.0806*	.0814*	.1689*	.0944+
	(2.35)	(2.14)	(2.09)	(2.34)	(2.24)	(2.12)	(2.55)	(2.27)	(1.99)
Adjusted R^2	.373	.308	.279	.408	.312	.255	.461	.377	.316
STD of MTB × Enforce	.0964**	.2743**	.1978**	.1134**	.3151**	.2200**	.1556**	.4100**	.2745**
	(3.61)	(3.62)	(3.75)	(3.46)	(3.75)	(3.61)	(3.86)	(4.13)	(4.11)
Adjusted R^2	.383	.318	.287	.422	.325	.265	.475	.390	.326

Note. Values are country-level results from equation (5). The dependent variable is the natural logarithm of 1 plus the number, proceeds, or proceeds per deal of equity issuance via initial public offering (IPO), seasoned equity offering (SEO), or IPO and SEO combined in an industry-country-year. All regressions include time-varying controls (interactions of the innovation measure with Enact, GDP per Capita, Stock/GDP, and Export to United States) and country-year and industry-year fixed effects. Robust t-statistics based on standard errors clustered at the country-year level are in parentheses. $N = 75{,}542$ for High Tech; $N = 75{,}310$ for Innovation Propensity; $N = 78{,}662$ for Intangibility; $N = 77{,}252$ for STD of MTB.

$^{+}$ $p < .10$.
* $p < .05$.
** $p < .01$.

innovative industries than in other industries after a country begins to enforce its insider-trading laws. Across the nine regressions, the estimated coefficient on High Tech × Enforce enters positively and significantly. The results are equally strong when examining the interaction term Innovation Propensity × Enforce. 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, enforcing insider-trading laws is associated with a 26 percent larger increase in the proceeds from IPOs in industries in which Innovation Propensity equals one than in industries in which it equals zero. As another example, the reported estimates suggest that when a country starts enforcing insider-trading laws, this is associated with a 13 percent larger boost in the financing proceeds from SEOs in industries with a naturally fast growth rate of R&D expenditures (that is, High Tech equals one) 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 in which the interaction term is Intangibility × Enforce or STD of MTB × Enforce. The interaction terms have positive and significant coefficients for the nine measures of equity issuances, which further supports the link between enforcing insider-trading laws and innovation via removing information asymmetries.[25]

6. Robustness Tests

6.1. Alternative Transformation of Dependent Variables

In our analyses, we follow the literature and use the natural logarithm of 1 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:

$$\begin{aligned}\text{Patent Count} &= \operatorname{arcsinh}(\text{Patent Count}^*)\\ &= \ln\left(\text{Patent Count}^* + \sqrt{\text{Patent Count}^{*2} + 1}\right);\end{aligned}$$

Patent Entities, Citation, PC Top 10 Percent, Generality, and Originality are similarly transformed. We then redo the analyses using the newly transformed mea-

[25] The results in Table 8 are robust if we exclude the period of the initial-public-offering bubble from 1999 to 2001 or if we focus on the post-1985 period, when the coverage of the Securities Data Company Platinum database expands.

sures of innovation. As shown in of Table 9, 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.

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.[26] We present the weighted regression results in Table 9. 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. *Additional Tests*

We conduct several additional tests to address remaining concerns with interpreting the results as reflecting the impact of enforcing insider-trading laws on innovation. First, to further alleviate concerns that zeros in the raw patenting data drive our results, we conducted the following two additional sensitivity analyses. First, we focused on the industries in the United States with more patents by calculating the total number of eventually granted patents filed in each industry-year in the United States and taking the time-series average of patent count in each industry as the measure of patenting intensity. Then we ranked the observations in our sample by this measure and designated industries that rank above the median, in the top 25 percent, and in the top 10 percent as having high levels of patenting activities. We discover that the positive effect of the enforcement of insider-trading laws on innovation remains significant in these subsamples. Second, we restricted the sample to observations for which the raw patent-based measures of innovation are greater than or equal to 1 and used the natural logarithm of these measures as our dependent variables. The results remain statistically robust and exhibit magnitudes similar to our core analyses. Then we determined that the results do not change when we use a Poisson model for the number of patents, which is a strict count variable at the country level.

Finally, we extended the analyses to evaluate 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 financing and 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) based

[26] 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.

Table 9

Robustness to Alternative Transformation of Innovation Measures and Weighted Regressions

	Inverse Hyperbolic Sine Transformation						Weighted Regressions					
	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality	Patent Count	Patent Entities	Citation	PC Top 10 Percent	Generality	Originality
Enforce	.1644*	.1245+	.2962*	.1332**	.1253**	.1983**	.1671*	.1230+	.2710**	.1172**	.1224**	.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)
N	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^2	.861	.870	.862	.733	.778	.780	.872	.882	.886	.756	.801	.803
High Tech × Enforce	.3638**	.3263**	.3034**	.2833**	.3325**	.3457**	.3105**	.2603**	.2356*	.2552**	.2957**	.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)
N	75,542	75,542	75,542	75,542	75,542	75,542	56,018	56,018	56,018	56,018	56,018	56,018
Adjusted R^2	.883	.891	.888	.757	.801	.812	.889	.900	.904	.771	.815	.825
Innovation Propensity × Enforce	.4183**	.3844**	.2803**	.3570**	.4096**	.4218**	.3661**	.3181**	.2298*	.3396**	.3768**	.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)
N	75,310	75,310	75,310	75,310	75,310	75,310	54,963	54,963	54,963	54,963	54,963	54,963
Adjusted R^2	.886	.895	.890	.766	.810	.819	.893	.904	.907	.781	.824	.833
Intangibility × Enforce	.1530**	.1364**	.1107*	.1661**	.1441**	.1551**	.1435**	.1221**	.0856+	.1600**	.1460**	.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)
N	78,662	78,662	78,662	78,662	78,662	78,662	57,269	57,269	57,269	57,269	57,269	57,269
Adjusted R^2	.877	.886	.883	.745	.786	.797	.886	.897	.902	.763	.805	.816
STD of MTB × Enforce	.1131*	.0873+	.1475*	.1436**	.1738**	.1657**	.0703	.0391	.0798	.1247**	.1391**	.1263**
	(2.28)	(1.84)	(2.29)	(3.94)	(4.21)	(4.13)	(1.57)	(.94)	(1.31)	(3.54)	(3.44)	(3.26)
N	77,252	77,252	77,252	77,252	77,252	77,252	56,996	56,996	56,996	56,996	56,996	56,996
Adjusted R^2	.878	.887	.885	.750	.795	.805	.886	.897	.902	.765	.809	.818

Note. For the weighted regressions, the dependent variable is the natural logarithm of 1 plus the raw value of innovation measures; regressions are weighted by the natural logarithm of firms' total assets in a country-industry. Regressions for Enforce include time-varying controls (Enact, GDP, GDP per Capita, Stock/GDP, Credit/GDP, and Export to United States) and country, industry, and year fixed effects. All other regressions include time-varying controls (interactions of the innovation measure with Enact, GDP per Capita, Stock/GDP, and Export to United States) and country-year and industry-year fixed effects. Robust t-statistics based on standard errors clustered at the country-year level are in parentheses.

$^{+}$ $p < .10$.
* $p < .05$.
** $p < .01$.

on US industries. We find that all of our results are robust to controlling for the interaction of Enforce and EFD and that the interaction enters positively and statistically significantly.

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. Using over 80,000 industry-country-year observations across 74 economies from 1976 to 2006, we discover that patent intensity, scope, impact, generality, and originality of patenting activity all rise markedly after a country first starts enforcing its insider-trading laws. Moreover, our findings link with 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 naturally innovative industries—industries that would experience rapid innovation if insider trading has not impeded accurate valuations—and 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 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 firms 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.

Our results 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 for 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.

Appendix A

Definitions of Variables

A1. Insider-Trading Law

Enforce. An indicator variable equal to one in the years after a country first enforces its insider-trading laws and zero otherwise (Bhattacharya and Daouk 2002).

Enact. An indicator variable equal to one in the years after a country enacts its insider-trading laws and zero otherwise (Bhattacharya and Daouk 2002).

A2. Patent-Based Measures of Innovation

Citation. The natural logarithm of 1 plus the total number of truncation-adjusted forward citations made to (eventually granted) patents in industry *i* that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*. The truncation-adjusted citation count is first summed over all of the patents in an IPC subclass and then converted to a two-digit SIC code (from PATSTAT).

*Citation**. Citation before the log transformation (from PATSTAT).

Citation^c. The natural logarithm of 1 plus the total number of truncation-adjusted forward citations made to (eventually granted) patents that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c* (from PATSTAT).

Generality. The natural logarithm of 1 plus the sum of the generality scores of all of the (eventually granted) patents in industry *i* that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*. The generality score of a patent is defined as 1 minus the Herfindahl index of the IPC sections of patents citing it. The higher the generality score, the more generally applicable the patent is to other types of innovations. The score is aggregated at the IPC level and then converted to a two-digit SIC code (from PATSTAT).

*Generality**. Generality before the log transformation (from PATSTAT).

Generality^c. The natural logarithm of 1 plus the sum of the generality scores of all of the (eventually granted) patents that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c* (from PATSTAT).

Originality. The natural logarithm of 1 plus the sum of the originality scores of all of the (eventually granted) patents in industry *i* that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*. The originality score of a patent is defined as 1 minus the Herfindahl index of the IPC sections of patents that it cites. The higher the originality score, the wider the range of technologies it draws on. The score is aggregated at the IPC subclass level and then converted to a two-digit SIC code (from PATSTAT).

*Originality**. Originality before the log transformation (from PATSTAT).

Originality^c. The natural logarithm of 1 plus the sum of the originality scores of all of the (eventually granted) patents that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c* (from PATSTAT).

Patent Count. The natural logarithm of 1 plus the total number of (eventually granted) patents in industry *i* that are filed with the patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*. The total number of patents is calculated at the IPC subclass level and then converted to a two-digit SIC code (from PATSTAT).

Patent Count.* Patent Count before the log transformation (from PATSTAT).

Patent Count^c. The natural logarithm of 1 plus the total number of (eventually granted) patents filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c* (from PATSTAT).

PC Top 10 Percent. The natural logarithm of 1 plus the total number of (eventually granted) patents in industry *i* that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*, where the total number of forward citations made to them are in the top 10 percent of the citation distribution of patents in the same IPC subclass and application year. The number is counted at the IPC subclass level and then converted to a two-digit SIC code (from PATSTAT).

PC Top 10 Percent.* PC Top 10 Percent before the log transformation (from PATSTAT).

PC Top 10 Percent^c. The natural logarithm of 1 plus the total number of (eventually granted) patents that are filed with patent offices in an OECD country and/or the EPO in year *t* by residents of country *c*, where the total number of forward citations made to them are in the top 10 percent of the citation distribution of patents filed in the same IPC subclass and application year (from PATSTAT).

Patent Entities. The natural logarithm of 1 plus the total number of distinct entities in country *c* that apply for (eventually granted) patents in industry *i* in year *t* with the patent offices in an OECD country and/or the EPO. The total number is calculated at the IPC subclass level and then converted to a two-digit SIC code (from PATSTAT).

Patent Entities.* Patent Entities before the log transformation (from PATSTAT).

Patent Entities^c. The natural logarithm of 1 plus the total number of distinct entities in country *c* that apply for (eventually granted) patents in year *t* with patent offices in an OECD country and/or the EPO (from PATSTAT).

A3. Country-Level Economic, Financial, and Legal Measures

Bank Privitization. A financial liberalization measure based on the presence of state ownership in the banking sector. 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 (Detragiache, Abiad, and Tressel 2008).

Bank Supervision. A financial liberalization measure based on the degree of banking-sector supervision, including capital-adequacy ratio and independence of the supervisory body. The measure 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 (Detragiache, Abiad, and Tressel 2008).

Capital Control. A financial liberalization measure based on restrictions on international capital flows and the existence of a unified exchange-rate system. 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 (Detragiache, Abiad, and Tressel 2008).

Central. An indicator that the political orientation of the largest party in the government is centrist (Cruz, Keefer, and Scartascini 2016).

Common Law. An indicator variable equal to one if the legal origin of a country is a common-law system and zero otherwise (La Porta et al. 1997).

Contract Enforcement. An index that measures the strength of legal enforcement of contracts, ranging from 0 (weakest) to 10 (strongest) (Gwartney, Lawson, and Hall 2015).

Credit/GDP. Domestic credit provided by the financial sector over GDP. 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 banks, and other financial corporations such as finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies (World Bank, WDI database).

Credit Control. A financial liberalization measure based on the strictness of credit control, including reserve requirements, existence of mandatory credit allocation, and credit ceilings. The measure is normalized between 0 and 3, with 0 indicating the least liberalized and 3 indicating fully liberalized (Detragiache, Abiad, and Tressel 2008).

Engineering Workforce. The number of technicians in R&D per 1 million people in a country-year. Data coverage starts with 1996 (World Bank, WDI database).

Entry Barriers. A financial liberalization measure based on the ease of foreign bank entry and the extent of competition in the domestic banking sector (such as restrictions on banking). 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 (Detragiache, Abiad, and Tressel 2008).

Fractionalization. The probability that two deputies picked at random from the legislature will be of different parties (Cruz, Keefer, and Scartascini 2016).

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 (Detragiache, Abiad, and Tressel 2008).

GDP. The natural logarithm of real GDP measured in 2005 US dollars (World Bank, WDI database).

GDP per Capita. The natural logarithm of real GDP per capita measured in 2005 US dollars (World Bank, WDI database).

Innovative Industry (Top 25 Percent). The fraction of innovative industries in a country-year. Industries with the number of patents per firm ranked in the top 25 percent of the sample are categorized as innovative. The number of firms in 2006 for each industry is used in the calculation (from PATSTAT and Orbis).

Innovative Industry (Top 10 Percent). The fraction of innovative industries in a country-year. Industries with the number of patents per firm ranked in the top 10 percent of the sample are categorized as innovative. The number of firms in 2006 for each industry is used in the calculation (from PATSTAT and Orbis).

Interest-Rate Control. A financial liberalization measure based on the extent of interest-rate liberalization, including that of deposit rates and lending rates. 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 (Detragiache, Abiad, and Tressel 2008).

IPR Protection. An index that measures the strength of national intellectual-property-rights protection, ranging from 0 (weakest) to 5 (strongest). The index is constructed as the unweighted sum of the scores in five subcategories for patent rights, namely, coverage of patentability, membership in international treaties, duration of protection, enforcement mechanisms, and restrictions on patent rights (Park 2008).

Left. An indicator that the political orientation of the largest party in the government is left-leaning, namely, left wing, socialist, communist, or social democrat (Cruz, Keefer, and Scartascini 2016).

Legal Integrity. An index that measures the strength and impartiality of the legal system and popular observance of the law, ranging from 0 (weakest) to 10 (strongest) (Gwartney, Lawson, and Hall 2015).

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. The measure is set to one for years after the official date and zero otherwise (Bekaert and Harvey 2000; Bekaert, Harvey, and Lundblad 2005).

Patent Law. An indicator variable equal to one in the years after a country enacts its first patent law and zero otherwise.[27]

Polity. A composite index indicating the level of democracy and autocracy, ranging from −10 (strongly autocratic) to 10 (strongly democratic) (Polity IV database).

PR and Legal Index. An index that measures the overall strength of the legal

[27] World Intellectual Property Organization, WIPO Lex Database (http://www.wipo.int/wipolex/en/).

system and property-rights protection, ranging from 0 (weakest) to 10 (strongest). The index is the average value over nine subindexes: 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 (Gwartney, Lawson, and Hall 2015).

PR Protection. An index that measures the strength of property-rights protection, ranging from 0 (weakest) to 10 (strongest) (Gwartney, Lawson, and Hall 2015).

Right. An indicator that the political orientation of the largest party in the government is right-leaning, namely, right wing, conservative, or Christian democratic (Cruz, Keefer, and Scartascini 2016).

Securities Market. A measure of the degree to which securities markets are liberalized. The measure codes on the a country's efforts to encourage the development of securities markets, including establishment of debt and equity markets, the auctioning of government securities, policies such as tax incentives and the development of depository and settlement systems to encourage these markets, development of a derivatives market and institutional investor base, and policies to promote 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 (Detragiache, Abiad, and Tressel 2008).

Stock/GDP. The value of listed shares as a fraction of GDP (Beck, Demirgüç-Kunt, and Levine 2010).

Trade/GDP. The import and export of goods and services as a fraction of GDP (World Bank, WDI database).

A4. Industry Characteristics

Export to the United States. The ratio of each industry's export to the United States to its country's total export to the United States in each year. The data are provided at the Standard International Trade Classification level (SITC Rev1),[28] and we map the data to the two-digit SIC level via harmonized system (H0) using the concordance schemes.[29]

High Tech. An indicator variable based on the high-tech intensiveness of each two-digit SIC industry. We calculate the average annual percentage of growth in R&D expenses (Compustat item xrd) over all US public firms in each industry-year. We then use the time-series average in each industry over the sample period (1976–2006) as the measurement of high-tech intensiveness at the industry level; High Tech equals one if it is above the sample median and zero otherwise (Compustat).

[28] United Nations, UN Comtrade Database (https://comtrade.un.org/data/).

[29] World Bank, World Integrated Trade Solution, Product Concordance (https://wits.worldbank.org/product_concordance.html).

Innovation Propensity. An indicator variable based on the innovation propensity measure for each two-digit SIC industry. We calculate the average number of patents filed by a US public firm in each three-digit US technological class in each year; we then calculate the time-series average in each technological class over the sample period (1976–2006). After obtaining the measurement at the three-digit technological class level, we convert it to the two-digit SIC level using the mapping scheme in Hsu, Tian, and Xu (2014); Innovation Propensity equals one if it is above the sample median and zero otherwise (Hall, Jaffe, and Trajtenberg 2001).

Intangibility. An indicator variable based on the proportion of intangible assets of each two-digit SIC industry. We calculate the average ratio of plant, property, and equipment (PPE; Compustat item ppent) over total assets (Compustat item at) across all US public firms in an industry-year. We then obtain the time-series average in each industry over the sample period (1976–2006) and compute 1 minus PPE/asset as the proxy for intangibility in each industry; Intangibility equals one if it is above the sample median and zero otherwise (Compustat).

STD of MTB. An indicator variable based on the standard deviation of market-to-book-equity ratio in each two-digit SIC industry. We calculate the standard deviation of market-to-book ratio (Compustat item (csho $\times$ prcc)/ceq) across all US public firms in each industry-year. We then compute the time-series average in each industry over the sample period (1976–2006) and divide the dispersion of market-to-book ratio at the industry level by the average market-to-book ratio in the same industry, where the denominator is firm-level market-to-book ratio averaged in each industry-year and then across industry-years; STD of MTB equals one if it is above the sample median and zero otherwise (Compustat).

A5. Equity-Issuance Measures

IPO Number. The natural logarithm of 1 plus the total number of IPOs in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

IPO Proceeds. The natural logarithm of 1 plus the total amount of proceeds (in millions of dollars) raised via IPO in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

Proceeds per IPO. The natural logarithm of 1 plus the average amount of proceeds per IPO (in millions of dollars) made in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

Proceeds per Issue. The natural logarithm of 1 plus the average amount of proceeds per equity issuance (in millions of dollars) made in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

Proceeds per SEO. The natural logarithm of 1 plus the average amount of proceeds per SEO (in millions of dollars) made in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

SEO Number. The natural logarithm of 1 plus the total number of SEOs in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

SEO Proceeds. The natural logarithm of 1 plus the total amount of proceeds (in millions of dollars) raised via SEO in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

Total Issue Number. The natural logarithm of 1 plus the total number of equity issuance in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

Total Proceeds. The natural logarithm of 1 plus the total amount of proceeds (in millions of dollars) raised from the equity market in an industry-country-year. Country is defined by the marketplace where the issuance is made; industry is defined at the two-digit SIC level (Thomson Reuters, Securities Data Company [SDC] Platinum database).

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