U.S. Innovation and Chinese Competition for Innovation Production

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Abstract

We propose that competitive shocks from China impact U.S. innovation through two distinct margins: the markets for innovation and existing products. We identify shocks to both using the geography of Chinese internet penetration and Chinese import data. Increases in the ability of Chinese industry peers to gather knowledge are followed by sharp reductions in U.S. R&D investment and subsequent patents, and increased patenting by Chinese firms. The new Chinese patents also cite the patents of treated U.S. firms at a high rate consistent with increased intellectual property competition. Overall, Chinese competition in intellectual property and in existing products influence U.S. firm innovation.

Keywords: Innovation, competition, China, investment, internet penetration.

JEL Codes: O31, O34, D43, F13

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China now has the wealth, commercial sophistication and technical expertise to make its pursuit of technological leadership work. The fundamental issue for the U.S. and other western nations, and the IT sector is how to respond ...

Office of the United States Trade Representative, March 28, 2018 report

1 Introduction

A growing body of research focuses on the impact of China's meteoric rise as an economic power and its impact on the innovation spending by established firms in the United States. This growing body of research has been matched by a growing interest in this same issue by policy makers, politicians and the popular press. Issues at stake include job loss, the incentives to innovate, and intellectual property protections. Yet the existing literature disagrees even on the most basic question. Does an increase in foreign competition have a positive or negative impact on the intensity of innovative investment in the U.S?

On the surface, increased competition is a negative shock and afflicted firms should reduce investment in R&D if this competition is in the form of strategic substitutes, as is true in many markets. Yet this prediction is not a given even if firms compete through strategic substitutes. For example, Aghion, Bloom, Blundell, Griffith, and Howitt (2005) suggest that firms might increase R&D following increased competition, as this might facilitate "escaping competition" through increased product differentiation. Bloom, Draca, and Van Reenen (2016) further predict that when firms have "trapped assets" that are difficult to redeploy, or high adjustment costs, these incentives to increase innovative spending increase further. In particular, these firms may maintain high ex ante production levels despite lower prices, if curtailing production is too costly. The increased innovative spending then restores some pricing power through differentiation. It is thus become an empirical question whether increased competition leads to increases or decreases in innovation spending.

The existing empirical evidence is also mixed. Autor, Dorn, Hanson, Pisano, and Shu (forthcoming) find a negative relation between competition shocks measured using trade data and R&D in the U.S. However, Bloom, Draca, and Van Reenen (2016) find that competition shocks (measured using trade data) lead to increased R&D spending in a sample of European firms. Hombert and Matray (2018) also examine U.S. firms, and find that firms that are ex ante R&D intensive experience more positive outcomes due to their increased ability to use R&D to escape competition. We consider a new approach to this question that examines competition in innovation itself and the impact of trapped assets. We also introduce a novel shock to the ability of Chinese firms to compete in knowledge creation based on the industry agglomeration geography of internet penetration growth in China.

We propose that global competition influences innovation through at least two competitive margins, each having different implications for innovation spending in the U.S. The first is examined by the existing studies: direct import competition in the market for existing products. These existing studies use tariffs and import data, reinforcing their focus on the margin of existing products. The second margin, which has not been studied in the U.S.-China innovation literature, is direct competition in the market for innovation and intellectual property itself. Importantly, shocks to tariffs and imports cannot be used as direct shocks to this margin, as both relate to products that already exist, and thus their impact on intellectual property (IP) competition would be indirect and observed with delay.

We study the impact of Chinese innovation and its competitive impact on U.S. innovation using direct measures of Chinese ability to access innovation in the U.S. over the internet. Traditional instruments such as tariffs and direct imports apply to existing product competition, and not competition in the race to create new technologies. We propose that industry agglomeration and internet penetration at the province level in China can be used to generate plausible exogenous variation in the capacity of Chinese firms to access information and challenge U.S. firm innovation in particular industries. First and foremost, intellectual property itself is a form of information, and the internet has proven to be an efficient means for accumulating knowledge, especially when the knowledge to be gathered resides overseas and is online in electronic form. Indeed a wealth of information on intellectual property, product market strategies, and the performance of U.S. firms is available online through the websites of U.S. regulatory agencies.

In our main analysis, we examine how U.S. firms change their innovative investment in the face of plausibly exogenous changes in intellectual property (IP) competition from China. We find that impacted U.S. firms significantly reduce spending in R&D over a three-year period after treatment. These firms realize fewer patents over the same horizon, and there is a material increase in Chinese patents in these same intellectual property production markets. In particular, there is a strong increase in new patents by Chinese inventors that directly cite the existing technology of the treated U.S. firms. This crowding-out effect is unique to China in our tests as placebo tests based on Europe and other major economies do not produce similar results. These results mitigate concerns that unobserved economic state variables may be driving our results.

Competition in the market for intellectual property likely has a strong industry-specific component. We thus use provincial industry production locations and motivation from the agglomeration literature to identify geographic regions where the most skilled and specialized human capital exists in China for a given industry. We build industry-specific measures of Chinese internet penetration by mapping province-level data on internet penetration to the primary industry locations in each province. Because internet penetration in different geographic regions depends on the ability of unrelated utility companies (internet service providers) to provide digital infrastructure, variation in this internet penetration is plausibly exogenous (particularly when we additionally control for industry growth rates in China). Intuitively, the provision of high quality internet depends in part on the distribution of population in that region, geographic features, and the relative efficiency of Independent Service Providers (ISPs) in different regions. Province-level penetration thus varies substantially across provinces and over time.[1] This framework allows us to create an industry-year panel of instruments for China's capacity to access innovation information that can plausibly challenge U.S. firms. In turn, this panel data approach allows us adequate power and variation

[1]Roberts and Whited (2013) suggest that variation along geographic dimensions has good properties regarding identification.

to test our key hypotheses even in the presence of rigid firm and year fixed effects.

Although we are careful to note limitations in our ability to fully establish causality, we conduct a number of tests that at least partially support the validity of our instrument. First, we find that our industry-year measures of Chinese internet penetration predict higher ex post incidence of U.S. firms complaining about competition from China, specifically complaints about Chinese competition related directly to technology and intellectual property in their 10-K documents filed with the SEC. Finding increased complaints about Chinese access to their technological and intellectual property is indicative of the second competitive margin of innovation noted above. In addition, placebo tests indicate no evidence of increases in similar complaints about competition in other regions of the world including Japan, Europe, and neighboring countries such as Canada and Mexico. This test is a strong placebo as complaints about competition from these other regions are more common unconditionally than are complaints about competition from China.

We thus expect significant increases in competition in the market for intellectual property coming directly from Chinese firms, but we should not see increases in competition coming from firms in other parts of the world. We find that our internet penetration measure strongly predicts higher rates of patent citations by Chinese inventors citing the patents of the treated U.S. firms in our sample. We observe no changes in citation rates by inventors from the other regions of the world. Finally, we also find higher rates of patents applied for in China itself that cite these same U.S. firm patents.

The results illustrate the mechanism driving intellectual property competition and indicate that omitted economic state variables, such as worldwide industry supply or demand factors, likely cannot explain our results. Our framework, which includes region, firm and time fixed effects, also ensures that identification is coming from specific Chinese provinces (mapped using industry agglomeration), and not from changes in China that are nationwide in scope. These findings support the validity of the exclusion requirement, as our instrument only measures shocks to innovative potential in China itself, and we only observe a strong impact on the specific U.S. firms that should be impacted.

Our hypothesis regarding the competitive margin of IP production predicts that our results should be stronger in specific subsamples. Because innovation is more important in industries with higher growth options, we first examine whether our results are stronger in industries with higher market-to-book ratios. As predicted, we find that firms with above-median market-to-book ratios experience more extreme ex post reductions in innovative investment and patents following competitive IP shocks from China.

A second prediction is that trapped assets will moderate these findings, as hypothesized by Bloom, Draca, and Van Reenen (2016). U.S. firms with more tangible or "trapped" assets have incentives to maintain high levels of innovation given high adjustment costs and that these firms should reduce innovation less when these competitive shocks materialize. We use the asset tangibility of U.S. firms as our measure of trapped assets and find that firms with more tangible assets do increase their relative R&D spending and patents in the face of increased competition to differentiate their products.

Our findings regarding growth options and trapped assets provide deeper insights on the importance of an industry's initial conditions, and how they shape the predictions regarding the impact of increased IP competition. These competing forces can help to explain much of the disagreement in the existing empirical literature, where both positive and negative competitive effects on innovation have been found. Key to our conclusion is that at least two margins of competition need to be separately explored. We find that direct competition in the market for intellectual property itself has a sharp negative impact on treated firms due to the intuitive crowding-out effect.

In contrast, if competition only increases in the market for existing products rather than in the market for IP production, it is more plausible that treated U.S. firms might increase innovation in order to escape competition. Such a strategy might be most optimal when, in fact, the Chinese competitors do not have the innovative capacity to compete on this second margin. For example, in such a market, ceding market share in the lowest quality existing products to the entrants, while increasing innovation in order to claim higher quality segments of the market for the incumbents, can form the basis for the post-shock equilibrium. This approach can restore some pricing power for incumbents, while accommodating the entering rivals in the market where their competitive advantage of lower cost labor might be most advantageous.

Although our focus is on competitive intensity in the market for innovation, it is natural to ask if our results inform the more controversial issue of intellectual property theft. A starting point is that IP theft and fair competition should have similar impact on treated U.S. firms. Both will crowd-out innovative spending as the foreign entrants claim a fraction of the rents for themselves. On the surface, the increase in patents we find suggests that IP theft is less likely, as the foreign innovators are securing legally defensible patent protection. However, this alone does not rule out IP theft as the ability to create the new patents might have roots in stolen trade secrets or other intellectual property as a precursor.

In order to at least partly inform whether our results relate to IP theft, we examine the extent to which U.S. firms complain directly about IP theft in their 10-Ks. We find suggestive evidence that our internet penetration instrument predicts a higher incidence of complaints about IP theft by the treated U.S. firms. This evidence suggests that IP theft, or "perceived IP theft," might explain part of the increased competition in these IP markets. Yet we caution readers not to draw strong conclusions from this analysis because power is limited and statements by firms about IP theft do not constitute direct proof that IP theft has in fact occurred. The underlying question of potential IP theft is important for future research to consider, as policy implications differ for IP theft versus high competition.

2 Literature and Hypotheses

Our study is rooted in product market globalization, and the competitive impact of foreign product market competition on innovation outcomes in a domestic market. We focus on the important case of U.S.-China competition and how it relates to innovation spending.

The existing global innovation literature typically focuses on the impact of competitive shocks in the market for existing products. We propose that foreign competition plays out on more than one competitive margin and that foreign competitors can challenge domestic firms both on pricing existing products, and by entering the competitive race for innovation.

Competition in the market for innovation in the domestic U.S. market has been extensively studied by many authors.[2] In an international context, Hombert and Matray (2018), Bloom, Draca, and Van Reenen (2016), and Autor, Dorn, Hanson, Pisano, and Shu (forthcoming) study the impact of competition from international trade on innovation. However, no study to our knowledge has examined the impact of product market globalization on the dual margins of competition in the existing product markets and in the market for innovation.

Globalization of product markets results in the opening of borders, and the impact on any nation can be modeled using theories of entry in markets with existing incumbents. In classical models of competition with strategic substitutes, such as the Cournot model, the central prediction is that an entrant will cause existing firms to downsize as the new competitor absorbs a fraction of the market share and applies upward pressure on quantities produced and downward pressure on prices. If the value of growth options in such a market is proportional to the scale of the firm, a natural follow-on prediction regarding innovation (our setting) is that such competitive shocks will also lead to reductions in ex-post innovation spending by incumbents as they reduce scale.

More recent research has challenged this classical view. Aghion, Bloom, Blundell, Griffith, and Howitt (2005) suggest that a shock to competition could result in increases in innovation as firms rush to differentiate their products in order to rebuild lost market power. This is the "escape competition" hypothesis. The validity of this alternative hypothesis depends at least in part on incumbent firms having a technological advantage relative to the new entrants, as only then would they be able to defend their differentiated products from entrants.

[2]Early work on innovation and competition has been summarized in the survey by Reinganum (1989) with recent contributions by Phillips and Zhdanov (2013) and Bena and Li (2014).

The classical theory and the escape competition theory thus have opposite predictions. It is therefore not surprising that existing studies find mixed evidence regarding the impact of Chinese competition on the innovation intensity of domestic firms. These studies, however, only examine one competitive margin: competition in the market for existing products. Indeed, on this margin, it is quite plausible that the ideal conditions for the escape competition strategy might hold in some markets.

How do these predictions change if the entrants are also adept at producing innovation? Examining this issue is our main contribution. We propose that the overall effect of Chinese competition and internet penetration on a domestic incumbent's innovation spending has two parts: (1) increased competition from the foreign rivals in the market for existing products and (2) increased competition from the foreign rivals in the market for innovation itself. The existing literature illustrates the ambiguous predictions regarding the former, whereas it is largely silent on the competition in intellectual property.

Our first hypothesis relates to the margin of competition for innovation, where we predict that increased competition from entrants on this same margin should crowd-out domestic firm innovation.

Hypothesis H1: Increased foreign competition will reduce the value of growth options and reduce incumbent domestic firm innovation spending in R&D and patenting. We also expect more patenting by the entering foreign firms, especially in technologies strongly related to the incumbent domestic firm's technologies.

Because H1 pertains to an increase in competition on the same margin that we are trying to predict (innovation), H1 intuitively predicts that the classic model's predictions of crowding out should dominate. In contrast, the scenario is more complex for the second margin: competition in the market for existing products with two potential competing forces.

Hypothesis H2a: Increased foreign competition in existing product markets leads domestic incumbents to downsize. We thus predict decreased innovation spending by these incumbent domestic firms.

Hypothesis H2b: Increased foreign competition in existing product markets leads to reduced prices for the existing products. To recapture pricing power, incumbent domestic firms will increase innovation spending in order to escape competition.

Because predictions regarding the impact of innovation in the market for existing products are ambiguous, it is natural to ask which hypothesis is more likely under different sets of initial conditions: H2a or H2b? We follow Bloom, Draca, and Van Reenen (2016) and propose that the existence of trapped assets by the domestic incumbents favors H2b. In particular, if a firm has assets that are not redeployable and adjustment costs are high, it follows that the firm has strong incentives to maintain high production levels. By increasing innovation, such a firm can preserve some pricing power despite its high production rate. This leads to our final hypothesis.

Hypothesis H3: When the domestic incumbent firms have high levels of existing non-redeployable assets, these firms will increase innovation spending, all else equal, to exploit their existing assets.

3 Data and Methods

3.1 Sample Selection and Panel Structure

Our sample begins with the universe of Compustat firm-years with available 10-K filings on the EDGAR system. We exclude financial firms and regulated utilities (SIC 6000 - 6999 and 4900 - 4949, respectively) and limit the sample to firm-years with sales and assets of at least $1 million. Since the Chinese internet penetration measures do not exhibit enough industry-province coverage until 2000, our final sample starts from 2001 and ends in 2016, with 62,899 firm-years from 8,584 unique firms. This panel is the base for our analyses.

We construct a set of country-specific competition complaint measures using texts in 10-K filings. For convenience, we utilize the software from meta Heuristica LLC to process our queries. To measure complaints about competition from China, we search for paragraphs that contain at least one word from both the country name list (”China” or ”Chinese”) and the competition word list (”compete” or ”competition” or ”competing”). We then use the number of matched paragraphs and normalize it by the total number of paragraphs in the 10-K document as our measure, CNComp. In addition to this generic competition measure, we further construct three additional competition measures by requiring the paragraph to contain a word from a third word list. First, to measure the intensity of competition, we construct the high competition measure, CNCompHi, by requiring the paragraph additionally contains one of the words in the following: (high OR intense OR significant OR face OR faces OR substantial OR significant OR continued OR vigorous OR strong OR aggressive OR fierce OR stiff OR extensive OR severe). Second, we measure the competition in intellectual property, CNIntComp, by requiring the paragraph to additionally contain both “intellectual” and “property” in the search. Finally, we measure complaints about intellectual property theft, CNIntTheft, by counting the number of paragraphs that match the country list, contain “intellectual property” or “trade secret”, and match one of the words in the following: (infringe* OR theft* OR stolen* OR steal*). In addition to constructing ratio measures of the total number of paragraphs, we also construct dummy variables which equal to one if we hit any matching paragraphs. Similarly, we also construct these measures for three other major economies in the world, namely Europe, North America (Canada and Mexico), and Japan, by changing the words in the country list. Details of these measures can be found in Table 13.

Other firm characteristics variables come from Compustat. We measure firms’ R&D intensities by normalizing the R&D expenses (`xrd`) by sales. Following the suggestions from Koh and Reeb (2015), we replace missing R&D intensities by the industry average (2-digit SIC) if the firm has applied for any patents in the past three years, and replace other missing values with 0. Definitions of other variables can be found in Table 13. Finally, we winsorize all ratio variables at the 1% and the 99% level to control for outliers.

3.2 Patent Data

We generate our patent measures from two sources. The first source is Google Patent. Since Oct. 31, 2017, Google, in collaboration with IFI Claims, a global patent research company, has made a set of structured and queryable datasets of patents available to the public[3]. The core part of the datasets contain over 90 million patent publications from the patent offices of 18 countries, including both the U.S. and China, among others. The same datasets support the searches made through patents.google.com, and to our knowledge represent one of the highest-quality sources for patent research. We also get the patent data from Kogan, Papanikolaou, Seru, and Stoffman (2016) (KPSS hereafter), who kindly shared the data on their website. The key advantage of the KPSS data is that the aforementioned authors have spent huge efforts to link the patents to U.S. public firms. However, the data ends in 2010, thus we will combine the two data sources to generate our patent variables.

We first use patent applications to measure firms' innovation activities. We extend the KPSS data with Google patent data. To link the new Google patent data to public firms, we utilize the links that are already developed by KPSS. First, we take the overlapping part of the Google data and the KPSS data[4] and generate links between permno numbers (from KPSS data) and (first) assignee names (from Google data). Next, we select all the utility patents that are filed in USPTO and granted after Nov. 1, 2010 from Google data. We then merge the permno number to the first assignee of patents using the link file we just generated. In this step we are able to match 77.4% of all the new patents.

Google data also provides the country information of the assignee[5]. Thus we are able

[3]More about this announcement at https://cloud.google.com/blog/products/gcp/google-patents-public-datasets-connecting-public-paid-and-private-patent-data. One can access the datasets through Google's BigQuery service

[4]The Google Patent Data covers 99.95% of the patents in the KPSS data matched by the patent number, and covers 99.59% of patents matched by both the patent number and the grant date.

[5]The corresponding variable is `assignee_harmonized.country_code` in the dataset.

to see patents that are assigned to foreign entities but filed in USPTO. We utilize the information by measuring the number of new Chinese patents that cite the existing patents of U.S. firms, providing direct evidence on the intensity of learning from Chinese firms. We also construct similar measures for other major economies, namely Japan, Europe, and Canada and Mexico. We use these measures as placebo tests to show that our internet penetration variable is not picking up omitted factors that attract general international competition.

Finally, Google data also includes all the patents filed in China's Patent Office, known as SIPO (State Intellectual Property Office of the Peoples Republic of China). Therefore we are also able to check whether patents filed by SIPO (by Chinese firms) also cite patents from U.S. firms, further enhancing our previous measure using only the patents filed in the U.S.

3.3 Internet Penetration

The quality and coverage of internet access in China has dramatically changed in the last two decades. While in the early 2000s, only fewer than 1% of the population in China had access to the internet, by 2018, the number of internet users in China has surpassed 800 million, and the internet penetration rate reached 57.7%. The internet has become the most important medium through which information is exchanged. For innovation activities, the internet enables inventors to collect information much more efficiently, and is almost a necessary component for any modern day research.

To measure the internet penetration rate in China, we hand collect the number of internet users from the reports issued by the China Internet Network Information Center (CNNIC). CNNIC is the official administrator of the internet infrastructure in China, and starting from 1998, it publishes semi-annual reports which describe the recent development of internet infrastructure and the demographics of internet users in China. To our advantage, these reports also provide the number of internet users separately for each province in China[6].

[6]The statistics does not include data for Hongkong or Macau.

We then collect the population numbers for each province from China Data Online[7] and compute the internet penetration ratio for each province in each year.

Note that the internet infrastructure has not grown at similar rates for all the provinces in each year. As one example, Figure 2 plots the year in which each province experienced its largest increase of the internet penetration ratio. The scattering pattern shows that the development of internet infrastructure is not always in sync for the whole nation. The landscape of the telecommunication industry in China has gone through drastic changes in the past two decades. Prior to 1994, China had one government department that provided all the phone and internet services: the Directorate General of Telecommunications, which was later registered as China Telecom. That monopolistic structure was changed in 1994 when China introduced China Unicom to compete with China Telecom. The deregulation continued in the 1990s as China Telecom was further broken up into two companies, and other new internet service providers like China Net and China Railnet were also established. By the end of 2001, China had seven companies in the telecommunication industry, and these companies tend to focus in different business areas and also different regions. For example, China Net, an internet service provider, mostly operates in the 10 provinces in the northern part of China. The drastic changes continued in the 2000s, as the industry went through a round of complicated consolidation, and by the end of 2008, only three companies, each of which now cover all the telecommunication business, were left, namely China Telecom, China Mobile, and China Unicom. These industry changes could generate a direct impact on the internet services. For example, we see from Figure 2 that after China Net was acquired by China Unicom in 2008, three northern provinces—Liaoning, Shandong, and Jilin—experienced their largest increase in the internet penetration rate in 2009.

For each U.S. firm, we want to measure the internet penetration for the potential peer firms in China. To do that, we use a weighted-average measure of the internet penetration of

[7] Unfortunately, the China Data Center at the University of Michigan has decided to terminate the service as of September, 2018. However, one can easily download similar data from alternative sources like http://data.stats.gov.cn/english/

the provinces where the industry of the U.S. firm is important. Indeed, a large literature has documented that industry tend to cluster geographically[8], and China is no exception. Ideally we would want the total assets of all the firms in each industry and province. However, such detailed census data is not publicly available, we thus retreat to the second best: using data from Chinese public firms. To help address the endogeneity of the industry-province links, we choose to use the industry- in year 2000. This choice is justified by our observation that the number of industries over which Chinese public firms span becomes sufficiently high and stable in year 2000, as shown in Figure 3. We select all the Chinese public firms that have non-missing headquarters and asset information in 2000. Our final sample includes 864 firms listed in mainland China (A-share), 74 firms listed in Hong Kong, and 5 firms listed in the US[9]. We then assign each firm to the province of its headquarters. To generate the weights, for each 2-digit SIC industry, we first calculate the weights of each province using the total assets of all its public firms in that industry. Then we exclude provinces whose weights are below 10%, and finally recalculate the weights using the remaining provinces. Figure 4 shows the weight loading for all the industry-province pairs.

Using the weights for each industry, we finally calculate the internet penetration measure as the weighted average across all provinces. In the next section, we show that our internet penetration measure significantly predicts the complaints from U.S. firms about competition in intellectual properties. We also find the measure will positively predict the number of Chinese patents that cite the U.S. firms' patents. As placebo tests, we find the internet measure does not predict the complaints about the competition and patent citations from other economies, suggesting our internet measure is not capturing the endogenous factors which affect the overall level of international competition.

Our results are robust to alternative constructions of the internet penetration measure which we present in Appendix B. We find results consistent to those with our main internet

[8]See Florence (1948); Hoover (1948); Fuchs (1962); Krugman (1993); Ellison and Glaeser (1997); Duranton and Overman (2005, 2008)

[9]For firms that are dual-listed, we only count it once using its primary exchange

penetration variable when we use the internet penetration from the top province which has the largest sales in the industry, instead of using a weighted-average measure. Second, we also find consistent results when we base industry agglomerations on macro-level industry output for each province.[10] Appendix B reports the results.

4 Summary Statistics and Validation

4.1 Summary Statistics

Table 1 presents summary statistics for our 2001 to 2016 panel of 62,899 firm-year observations having machine-readable 10-K filings. On average, the weighted internet penetration ratio is 36% for each firm-year. We see that about 5% of sample firms explicitly complain about competition from China, and 40% of them specifically mention intellectual property in their complaints. The incidence of U.S. firms complaining about competition, and especially competition in the market for intellectual property, also has been rising. Figure 1 plots the time-series of the general Chinese competition complaint measure and the complaint measure about IP competition. Both measures show tremendous increases over the years.

Table 1 not only indicates we have ample power to examine the impact of Chinese innovative capacity on U.S. firms, it also indicates that we have even more power to run placebo tests. For example, sample-wide, U.S. firms complain about European and North American (Canada and Mexico) competition at even higher rates. As shown in Table 1, the Chinese competition (scaled by document size and x 1000) variable averages 0.15, whereas the analogous variable for Europe is 0.26 and it is 0.24 for North America. Because we use activity in other parts of the world as placebo tests, this indicates that there is ample power to detect deviations from the exclusion requirement using these other regions of the world as placebos. However, this variable is just 0.04 for Japan, indicating its smaller economic size.

[10]The data is based on Chinese census and we acquire the data from China Data Online. One disadvantage of the data is that it only includes manufacturing industries.

When we consider other regions of the world in our placebo tests for patent citation activity, the average intensity of Chinese firms citing U.S. patents is 2.36, while European, Japan and North American citations of U.S. firms are 26.85, 23.88 and 5.06, respectively. Our identifying assumption is that Chinese internet penetration is first-order driven by the capacity of unrelated IP providers in China and their capacity to expand. If so, our main results should not be driven by underlying state variables such as time-varying industry demand shocks.

Because demand shocks have a global component to them, it follows that if our identifying assumptions are violated, our Chinese internet penetration variable should also predict growth in European, Japanese, and North American firms citing the same U.S. firms. Hence we use these regional activities as placebo tests. Because the data is much richer for these regions than it is for China, it follows that these placebo tests should be particularly strong in terms of the power to detect violations of the exclusion requirement. As we document later, we find strong results for Chinese companies and no results for placebo tests using the other regions of the world.

Table 2 displays summary statistics at the firm level rather than at the firm-year panel level (Table 1). In particular, we first calculate the mean value of each variable for each firm, and the table represents the statistics for the resulting firm averages. The primary motive for reporting summary statistics in both dimensions is to examine the distributions of our key variables, especially the more extreme values. As we will include firm and year fixed effects, for example, major outliers could sway our findings.

As is well known in the innovation literature, many variables measuring R&D and patenting activity have distributions that tend to be right-skewed. Consistent with the literature, we therefore winsorize all of our key variables at the 1%/99% level[11]. Overall, we find distributions that are similar to those in other studies. Although these distributions are consistent with other studies, in Appendix B, we also examine robustness tests to determine if our re-

[11]We winsorize three variables CNIntTheft %, CNIntTheft Dummy, and JPIntComp %, at the 0.1% and 99.9% levels because these variables have values of 0 at the 99th percentiles.

sults remain robust in key subsamples including the set of firms with positive R&D activity or in subsamples with above-median patenting activity. Our results remain highly robust.

4.2 Validation Test: EDGAR Downloads by Chinese Internet Users

In this section, we examine the informativeness and relevance of our measure of industry-specific Chinese internet penetration. In particular, we test whether this measure predicts higher observed rates of Chinese internet users downloading information about U.S. firms in specific industries (and in specific years). For example, if internet penetration increases in a Chinese province that focuses on electronics production in 2006, we predict that U.S. firms in the electronics industry will experience increased downloads by by Chinese internet users specifically in this year. If additionally, the evolution of internet penetration in China is plausibly exogenous relative to industry conditions, we additionally predict no relationship with downloads by internet users in other (placebo) nations. Alternatively, if internet penetration was endogenously driven by industry conditions, we instead would predict a strong link to internet downloads from many parts of the world as industry conditions are highly correlated across nations.

We test these predictions using the EDGAR internet log files from the U.S. Securities and Exchange Commission. We use the IP Address of each visitor to identify which nation they are from, and we then tabulate the number of visitors from each nation to each individual U.S. public firm in each year from 2004 to 2015. We exclude IP addresses that are possibly web crawler. Following Lee, Ma, and Wang (2015), we tag an IP address as a web crawler if the IP address has downloaded files from over 50 or more firms in a day[12]. As larger firms will have more visitors, we scale the total web visits by each firm's sales to create our key dependent variable: # of EDGAR searches/sales. We also standardize this variable in each year for the ease of interpretation. We estimate the following regression

[12] In addition to excluding the requests from web crawlers, we also exclude web requests that (1) have a server code larger than 300 and (2) are on the index pages.

$$Y_{it} = \beta CNInternet_{it-1} + \boldsymbol{\gamma} \boldsymbol{Z_{it-1}} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{1}$$

The dependent variable is the EDGAR web visitor traffic measure described above. Detailed definitions of these variables can be found in Section 3.1 or Table 13. CNInternet is our key measure of competition and is the weighted-average internet penetration across provinces where Chinese firms agglomerate at the industry level. $\boldsymbol{Z}$ represents the control variables, which include: CNSalesGR, the sales growth of the same 2-digit SIC industry in China, log(10kSize), log of the total number of paragraphs of each 10-K filing, firm age, and size (log(total asset)). We also include industry Q, computed as the product-similarity-weighted average Q of the firm's TNIC industry peers. Finally to control for domestic competition, we include the total similarity (sum of TNIC similarity scores) over a firm's industry rivals using the TNIC network. All independent variables are lagged one year relative to the dependent variable and hence are ex-ante measurable. We also include firm and year fixed effects in all regressions, and the standard errors are clustered by firm.

Panel A of Table 3 shows that our measure of industry-specific Chinese internet penetration significantly predicts the intensity of EDGAR downloads for U.S. firms in the treated industry by Chinese internet users. The inclusion of firm fixed effects absorbs all firm-specific unobservable characteristics, and allows us to focus on the most rigorous within-firm effects. These results provide strong evidence of our proposed mechanism: internet usage is a major tool for rapid information gathering of knowledge capital by overseas firms. This, in turn, exposes treated firms to increased competition from abroad specifically in the market for innovation and knowledge itself. These findings also indicate an unintended consequence of mandatory disclosure. Such disclosure can strengthen competition from overseas, likely at the expense of domestic firms.

Panel A of Table 3 also reports the results of our placebo tests, where we consider EDGAR searches from other major economies. As predicted, we find no significant link to our measure of Chinese internet penetration for the European Union, Japan, or Canada and Mexico. These results are consistent with Chinese internet penetration being driven by factors that are plausibly exogenous relative to industry state variables. In particular, if internet penetration was correlated with industry demand or expected growth, which have a common global component, we would expect these placebo tests to fail. Our findings thus suggest that any link between internet penetration and industry conditions is likely small or negligible in magnitude.

Panel B of Table 3 reproduces the tests in Panel A using our measure of internet penetration based only on Chinese corporations that only trade via domestic A-shares (we thus exclude firms listed in Hong Kong or in the United States). Although this restriction can reduce power, we also note that these purely domestic firms likely have fewer options for gathering information outside of the internet. The results in Panel B are similar but slightly stronger than those in Panel A indicating that our results using either approach.

4.3 Validation Test: Complaints about Chinese Competition

In this section, we examine the following question: if elevated levels of industry-specific Chinese internet penetration are associated with higher ex-post complaints by U.S. firms, does that mean they are facing higher levels of competition specifically from Chinese firms? We use textual analysis of 10-Ks disclosed by U.S. firms during our sample period as explained earlier.

As our hypothesis is that internet penetration specifically shifts competitive intensity in the market for intellectual property production, we also go one step further. We also measure the intensity of U.S. firm complaints about competition that appear specifically in paragraphs where the company is discussing innovation. We predict positive results, and such would serve to validate the economic content of our primary internet penetration variable.

An analogous framework for other major economies (excluding China) allows us to further examine the exclusion requirement using placebo tests. We examine if our Chinese internet penetration variable also predicts higher rates of complaints by U.S. firms about competition from Europe, North America (Canada and Mexico) and Japan. If the exclusion requirement holds, and if our internet penetration variable is not related to underlying state variables relating to industry supply or demand shocks, then we predict that these placebo tests should produce insignificant results. As noted earlier, these placebo tests have high power due to the fact that these other economic regions are large in scale and hence U.S. firms frequently summarize the intensity of competition from these regions. The key empirical question is if these complaints are also related to Chinese internet penetration.

Table 4 shows the results. In the first two columns, we find that the Internet penetration significantly predicts the rate at which treated U.S. firms in the same industry complain about competition specifically from Chinese firms. A one standard deviation increase of the internet penetration ratio leads to a 0.122 standard deviation increase, or a 63% increase from the sample mean of the Chinese competition complaint measure. We obtain similar estimates if the dependent variable is a dummy equal to one if the given U.S. firm has at least one complaint in its 10-K. Columns (3) and (4) of Table 4 show that the high competition measure is also significantly predicted by the internet penetration measure.

Our most direct tests are in the last four columns of Table 4. We find that internet penetration also significantly predicts U.S. firm complaints about competition that are specifically related to intellectual properties (IP) (see Columns (5) and (6)). In Columns (7) and (8), instead of focusing on competition, we consider instances where U.S. firms discuss IP theft. This reflects the fact that IP theft, in an economic sense, is a form of competition and U.S. firm complaints should thus follow similar patterns. We find that indeed they do.

The possibility of IP theft has been a centerpiece of recent public and political debates about recent trade conflicts between the U.S. and China. Although we do not draw any strong conclusions with respect to IP theft, our finding that internet penetration significantly predicts IP theft complaints from U.S. firms is suggestive. IP theft, or "perceived IP theft," might thus explain part of the increased competition observed in these IP markets. However, we caution that complaints in 10-Ks do not constitute any proof that any IP theft has, in fact, occurred. Moreover, we do document increased patenting by Chinese firms (discussed later), which is not a form of theft given that patents are both transparent and legal. Yet IP theft could be a precursor to such patents, as the younger firms in China might use trade secret theft to catch up on overall knowledge capital, which is necessary for patents. Overall, our evidence of IP theft is not decisive and this suggestive evidence and the importance of the question indicates that future research examining this issue would be invaluable.

Overall, Table 4 shows that industry-specific internet penetration in China strongly predicts ex-post complaints about competition from U.S. firms, especially competition on the margin of innovation itself. This validation test indicates that the economic content of our key internet penetration variable is in line with our predictions.

4.4 Placebo Tests using Other Major Economies

Although the validation documented in the preceding section indicates positive information about content, other economic forces might also affect firm innovation and be correlated with Chinese internet penetration. For example, industry-specific internet penetration might be correlated with global supply or demand shocks in the given industry, or it might relate to global competition more than just Chinese competition alone. In order for our experiment to be ideal, this variable should only identify shifts in the capacity of Chinese firms alone to challenge firms globally on the competitive margin of innovation.

To further examine the exclusion requirement, we construct analogous competition complaint measures for other major economies, namely Japan, Europe, and neighboring countries in North America (Canada and Mexico). If the internet penetration variable contains information about the industry's state, thus violating exclusion, we would expect that complaints about competition from these other economies would show similar positive signs. Table 5 shows the results. In Panel (A), we run similar regressions based on Equation 1, but replace the dependent variable with the complaint measures from other countries. For brevity we focus on complaints about competition and intellectual property theft.

Columns (1) - (4) of Table 5 show that Chinese internet penetration is not significantly related to complaints about competition from Japan or North America. However, Columns (5) and (6) show weakly significant results for the European Union, indicating some potential concerns about exclusion. We examined this issue in-depth and the results indicate that this result is likely spurious. First, the significance of the European Union results is driven fully by the first year of our sample, likely indicating an outlier perhaps relating to the formation of the European Union. If we exclude the first year, the results for the European Union are insignificant whereas our results for China are highly robust.

A second key issue is that our primary measures of industry agglomeration at the province level in China use geographic headquarters location data from all publicly traded Chinese firms, including those listed in China, Hong Kong, and in the United States. If there is a violation of the exclusion requirement, a most likely source could be that Chinese firms that list in Hong Kong or in the U.S. have better access to information about innovation in their industries, creating channels for information transmission outside of the internet.

We test this issue in Panel (B) of Table 5. In particular, we re-define Internet penetration using industry-specific agglomeration data based *only* on Chinese firms listed in Mainland China (those having A-shares). This more narrow definition of internet penetration does not load on companies having listings outside of China, and hence limits any alternative channels for information transmission beyond the internet. The results in Panel B lend support to this explanation of the results in Panel A. In particular, all of the placebo tests from all three major economies are insignificantly related to Chinese internet penetration. Although the results in Panel A for the European Union might be spurious and thus less relevant, the results in Panel B indicate a very conservative strategy for our main tests in the paper.

In particular, we run all tests in the paper using our main internet penetration variable and also separately using our mainland-China-only internet penetration variable. We note that all of our results are robust in both specifications. Moreover, our results are actually stronger using the mainland-China-only measure. For this reason, we report results using the complete internet penetration measure in order to be conservative, although all results are robust to either model.

We briefly note that we later run an additional placebo test later in the paper when we consider patenting activity. We find even stronger support for the exclusion requirement in all of these tests. In particular, our main result is that Chinese firms increase their patenting activity in the markets of the treated U.S. firms after episodes where internet penetration increases. They also greatly increase cites to the treated U.S. firms in their same industry. The key placebo test we consider later is whether European, North American or Japanese firms do the same. If the exclusion requirement did not hold, we would expect similar results as explained above. As we explain later, we find no significant results for these other economies, and these placebo tests hold regardless of whether we define Internet penetration using all Chinese firms or just those listed in mainland China. As discussed in our summary statistics section, these tests are particularly strong placebo tests due to the fact that patenting activity overall is more intense for firms from Europe, Japan and North America relative to China.

Collectively, these placebo tests suggest that it is unlikely that our internet penetration variable is contaminated by a global factor or by an omitted industry state variable relating to supply or demand shocks. These findings lend support to the possibility that our results are consistent with internet penetration causing reductions in innovative activities of treated U.S. firms due to a crowding-out effect of increased foreign competition in the market for innovative technologies.

5 Competition and Innovation

In this section, we examine how competition from China, as measured by our industry-specific Chinese internet penetration variable, affects the innovation activities of U.S. firms.

5.1 Impact on U.S. Firms

We first examine how ex ante industry-specific Chinese internet penetration impacts ex post investment in R&D expenses by treated U.S. firms. We do so by estimating a regression model as specified in Equation 1. Our key dependent variables are the R&D/sales and the number of patents/sales of our U.S. firms.

Table 6 shows the results. Column (1), which uses R&D expenses in year t+1 over sales in year t as the dependent variable, shows that internet penetration significantly negatively predicts ex-post R&D. The coefficient estimate of -0.188 is significant at the 1% level, and indicates that the R&D expense ratio decreases by 0.188 standard deviations when Chinese internet penetration increases by one standard deviation. The coefficient remains significant when we examine the two-year ahead R&D activities in Column (2) and three-year ahead R&D in Column (3). To ensure the result is not driven by changes in the denominator (the scaling factor sales), following convention, we scale both dependent variables by the ex ante value of sales from year t.

We find a similar result for the ex post patenting activities of the treated U.S. firms. In Columns (4) - (6) of Table 6, we use the number of patent applications in the next three years divided by sales in year t as the dependent variable. Column (4) shows a highly significant coefficient estimate of -0.105, indicating a decrease of 0.105 standard deviations of patenting activities when Chinese internet penetration increases by one standard deviation. In years two and three, we continue to observe significant and negative coefficients.

To ensure that our results are not driven by the skewed distribution of R&D and patents, we re-estimate the model using Poisson regressions. Table 8 displays the results. To facilitate the Poisson regressions, we drop the firm fixed effects and instead we control for the lagged dependent variable. Overall the negative effects we find for internet penetration on ex post U.S. firm innovation are analogous to those in Table 6. In Table 16 of Appendix B, we also find consistent results when we only include observations with positive R&D expenses. Collectively, it is unlikely that the skewed distribution of R&D can explain our results.

We thus conclude that plausibly exogenous shocks to the ability of Chinese firms to compete in the market for innovation production are associated with sharp reductions in the ex-post innovation rates of treated U.S. firms. This first main result in our paper is new to the literature, which instead focuses on the margin of competition in the production of existing products.

5.2 Impact on Chinese Firms

We now examine the relationship between ex ante industry-specific internet penetration and ex post increases in the number of new Chinese patents that directly cite the existing patents of the impacted U.S. firms. We utilize the country information of the first assignee for each patent to identify patents that are assigned to a Chinese entity. For each firm i in year $t+1$, we then count the number of new patents that are (1) applied for through the USPTO, (2) assigned to a Chinese entity, and (3) cite any existing patents of firm i. Following our standard conventions, we then scale this count (PatCiteUS$_{CN}$) by firm sales in year t.

We use this measure of new Chinese patents (that cite pre-existing same-industry U.S. firm patents) as the dependent variable in our next set of tests. The results are displayed in Table 9. Columns (1) - (3) of Table 9 show that ex ante internet penetration predicts increases in the number of Chinese firms citing patents to these U.S. firms in the next three years. Results are significant at the 1% level in each of the three ex post years. The effects are also large as a one standard deviation increase in internet penetration is followed by a 0.288 standard deviation increase in the number of citing patents by Chinese firms in the following year.

To ensure that our tests are not driven by changes in the overall intensity of patents to a given U.S. firm's existing patents, we consider an alternative scaling that accounts for the cites to these same patents by other U.S. firms. In particular, we define PatCiteUS$_{US}$ as the number of cites to the focal firm's patents by U.S. firms. Columns (4) - (6) of Table 9 show the results of regressions where the dependent variable is PatCiteUS$_{CN}$ / (PatCiteUS$_{CN}$ +

PatCiteUS_{US} + 1). The added one in the denominator avoids division by zero and this construction ensures this variable is bounded in [0,1] and thus does not have outliers. We find that the results in Columns (4) to (6) are very similar to our baseline results in Columns (1) to (3). Our results are thus not driven by broad increases in patent cites, but rather are unique to the Chinese firms citing these patents.

The Google patent database also includes all patents filed with SIPO, the Chinese Patent Office. We thus construct a similar measure of Chinese patents that cite the U.S. firm patents, but that are filed in China. The dependent variable for Columns (7) - (9) of Table 9 is PatCiteCN, which is the number of new patents that are applied with SIPO that cite the existing patents of the U.S. firm, and we scale this quantity by the focal firm's sales. We find that the coefficient estimates for internet penetration once again are highly significant and economically large. A one standard deviation increase in internet penetration is associated with an increase of 0.180 to 0.250 standard deviations of these SIPO patents over the three ex post years.

Columns (10) - (12) of Table 9 repeat this exercise using the same scaling convention discussed above for Columns (4) to (6), where the goal is to ensure our results are not explained by broad-based increases in cites to the focal U.S. firm's patents. Our results remain significantly positive in all three years.

Overall, we find consistent evidence that the internet penetration predicts strong ex post patenting activity by Chinese firms, and that these new patents are directly in the technological areas previously covered by the treated U.S. firms. These results suggest that high quality internet access facilitates increased learning by Chinese firms about the existing technologies used by U.S. firms in their industry. Put together with our finding that U.S. firms decrease patenting in these same technological markets, our results suggest that internet penetration is followed by a strong crowding-out effect. As Chinese firms enter these markets for innovation, they absorb a fraction of the associated rents, and thus crowd-out the treated U.S. firms.

5.3 Impact on Firms in Placebo Economies

Analogous to our earlier placebo tests in Table 5 that examined complaints by U.S. firms about competition from rivals in various economic centers, we perform a similar set of placebo tests regarding the ex post patenting results we found for Chinese firms in the previous section.

If the exclusion requirement is strongly violated, we would expect to see significant increases in patenting activity that cites these same U.S. firms by other firms in other major economies including Europe, North America and Japan. As noted earlier in our summary statistics section, these placebo tests are strong due to the fact that patenting activity by firms in these other regions is more active in our sample overall than is patenting activity by Chinese firms. Even if relatively modest industry supply and demand effects were driving our results, these placebo tests should produce significant links to our Chinese internet penetration variable for firms in these economies.

We therefore consider regressions analogous to those in Table 9, except that we replace the dependent variable with patenting activity associated with firms in each of these alternative economies. Table 10 displays the results. In Columns (1) to (3), the dependent variable is based on patents filed with USPTO by assigned entities in Japan. Columns (4) to (6) are based on North American entities and (7) to (12) are based on European Union entities.

The results in Table 9 show that, across all columns and thus all economic regions, we find no evidence that our Chinese internet penetration variable predicts ex post patenting activity by firms in these regions. The absence of results also holds uniformly over the first, second and third years following the increases in internet penetration.

Furthermore, the economic size of the coefficients are much smaller than those for Chinese patents documented earlier. In fact, six of the nine regressions show a negative sign, whereas the results for China are positive and highly significant. Especially when combined with our results for Table 5, these placebo tests indicate that our internet penetration measure rather cleanly measures the ability of Chinese firms uniquely to compete in the market for innovation at a global level. We find no impact for firms in other nations, suggesting that the exclusion requirement likely holds in a first order way.

5.4 Competition in Innovation vs. Product Market Competition

To contrast between the two margins of competition, we follow the literature and use import penetration from China to measure China's competition in existing products. See Appendix 6 for detailed steps regarding how we construct the import penetration variable. We then consider regressions that jointly include both competition in existing products and competition in innovation (based on our standard internet penetration variable). Panel A of Table 7 displays the results. The dependent variables are the R&D expenses in year $t + 1$ scaled by sales in year t, as well as the number of patents in year $t + 1$ scaled by sales in year t. Columns (1)-(4) show the results for R&D expenses. In Columns (1)-(3), we use an early part of our sample (2001 - 2007) to better match the sample period used in Autor, Dorn, Hanson, Pisano, and Shu (forthcoming) (ADHPS hereafter). We include only the internet penetration variable or the import penetration variable in Columns (1) and (2), and include both competition variables in Column (3). Comparing the coefficient estimates of two competition measures in Columns (1), (2) and (3), we find the coefficient estimates are of similar magnitudes, suggesting that the two measures of competition are distinct and are not highly correlated. While both competition variables show negative coefficient estimates, only the coefficient for CNInternet is significant. We find a similar result when we repeat the analysis using the full sample (2001 - 2016) in Column (4).

Columns (5) to (8) examining patenting activity. We do find that Chinese import flows impact U.S. firms' patenting activity, in particular in the years right after China's admission into the WTO in 2001. We see that CNInternet has a negative but insignificant coefficient estimate in Column (5) of Panel A, while the CNImport shows a significant and negative estimate in that early sample. The results are similar when we include both competition variables in Column (7) - however the CNImport is significant and negative while the CNImport variable is insignificant. This result points to the large impact of imports after China's inclusion into the WTO in December, 2001. In sharp contrast, when we extend the sample to 2001 to 2016, we see that the coefficient estimate for CNInternet remains negative and becomes significant, while the coefficient for CNImport loses its significance. Columns (3) - (4) in Panel B show that the CNImport variable is negative and significant for patenting activity when we only include the CNImport variable.

Thus for R&D and for patenting over the full period, including the impact of flows of physical imports into the U.S. does not reduce the separate impact of competition in innovation from increased access to information via the internet that is shown in columns (4) and (8).

We further examine specifications that include CNImport alone and in different sample periods in Panel B of Table 7. Consistent with ADHPS, we find significant and consistent negative effects for CNImport when it is included in the regression without CNinternet. In particular, column (1) shows a significant and negative coefficient estimate using the sample period 1997-2007 used in ADHPS.[13] In Column (2), we find a similarly negative and significant coefficient estimate when using the portion of this sample that overlaps with our sample period (2001 - 2016).

The evidence suggests that, in our sample, which is more recent than existing studies, competition relating to innovation is growing in importance relative to competition from existing products, which we con rm is highly significant in earlier samples. This shift in later years is also consistent with Chinese import penetration reaching more stable levels in later years, and hence our rigid effects absorb more of its variation. Importantly, our results should not be interpreted as import penetration not being important. Rather, our more recent sample is best suited to explore competition from innovation, and earlier samples are better suited to examine import penetration.

[13]We use the period 2001-2007 in the tests in Panel A because this avoids the financial crisis years and also because the CNInternet variable is of high quality only after 2001 (See Section 3 and Figure 3).

5.5 Competition and Asset Composition

As we noted in our discussion of hypotheses, the impact of foreign competition on the innovation activities of U.S. firms can vary based on the specific threats posed by the foreign entrants, and also based on the asset composition of the affected U.S. firms. For example, theory suggests that competition in the market for existing products can either increase or decrease innovation activities by affected U.S. firms. Moreover, U.S. firms having non-redeployable assets might have particularly strong incentives to increase innovation spending on the margin. In particular, innovation can help firms "escape competition" and serve higher quality market segments while conceding low quality segments to the entrants.

5.5.1 High versus Low Growth Options

Because our primary focus is on competition in the market for innovation, it also follows that our predictions should be particularly strong for U.S. firms that have stronger growth options, as innovation is a large fraction of firm value for these firms. Analogously, firms with few growth options are likely more impacted by competition in the market for existing products.

We first examine whether our results are stronger for U.S. firms with high versus low growth options as measured by each firm's market-to-book ratio. To do so, we start with the models we ran in prior sections of this study, but add an interaction between the internet dummy and an additional dummy variable, HighQ, which equals to one if the firm has an above-median industry market-to-book ratio in the prior year. We also include the HighQ dummy itself in the model. The dependent variables include the complaint measures from Table 4, and the innovation measures from Table 6. Table 11 shows the results.

Columns (1) to (3) show that higher market-to-book firms complain more about competition from China, and complain more in the context of paragraphs discussing innovation. As documented in the existing literature, these high valuation firms tend to have more growth options and are more innovative. As a result, their overall valuations load highly on their ability to control markets for innovation in their sectors, and direct competition from Chinese peers on the margin of innovation production should be particularly relevant. The coefficient of the interaction term is generally one-third as large as the coefficient of the internet penetration level alone, suggesting an economically large difference between the high Q and low Q firms.

We also find that these high value firms have innovation activities that are also more sensitive to Chinese internet penetration. As shown in Columns (4) to (7), these high market-to-book ratio firms more severely scale back on their R&D expenses and patenting activities when internet penetration is high. The coefficient of the interaction term for R&D in Column (4) is -0.062, almost half the size of the coefficient of the internet penetration variable itself, which is -0.152. The effect is also economically large for patenting activities.

We conclude that our results for competition in the market for innovation are stronger for U.S. firms that that have more valuable growth options and thus more potential exposure to competitive threats that are uniquely in the market for innovation production.

5.5.2 Trapped Assets

The theory of Bloom, Draca, and Van Reenen (2016) suggests that firms with more trapped assets (assets with a high adjustment cost to redeploy) will have stronger incentives to increase innovation following shocks to competition. This is due to the possibility that innovation can facilitate an escape from competition into higher-quality market segments (Aghion, Bloom, Blundell, Griffith, and Howitt (2005)). When competition increases, the affected firms become more innovative even if they were not highly innovative before the shock's arrival. The prediction is that U.S. firms will increase innovation following such competitive shocks.

We now test whether the likely existence of trapped assets also favors higher innovation levels for the affected U.S. firms as the aforementioned theories predict. We measure the likely existence of trapped assets using the level of asset tangibility of the U.S. firms. We then consider regressions similar to those in the previous section, but we interact internet penetration with a dummy indicating above-median asset tangibility in the prior year (instead of a high market-to-book dummy).

Table 12 displays the results. Columns (1) to (3) show that firms with higher asset tangibility complain more about the Chinese competition. This supports the notion that these firms face fewer options to adapt to the increased competition because they cannot easily downsize as some theories would predict. These results are consistent with the existence of trapped assets. Moreover, despite these additional complaints, we find that high asset tangibility firms favor increases in innovation relative to firms with less asset tangibility as the cross terms in Columns (4) to (7) are all positive and highly significant at the 1% level or the 5% level. These findings are consistent with the possibility of increased innovation to plausibly escape competition.

Although these results support the theories of Bloom, Draca, and Van Reenen (2016) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) for this well-motivated subsample, we note that our broader results show that this outcome is not observed in all situations. In particular, the sample-wide results strongly favor down-sizing of innovative activities when the competitive shock is in the market for innovation production.

Overall, our analysis of two competitive margins—competition in innovation and competition in existing products—plus accounting for the role of asset composition of the treated U.S. firms, helps to explain much of the disagreement in the literature regarding the impact of foreign competition on U.S. firms' innovative activities. Collectively, our results stress the importance of analyzing competition on multiple margins when the competitive threats are more nuanced. Our results also indicate the importance of initial conditions such as asset composition, as these characteristics strongly moderate the incentives to increase or decrease innovation.

6 Conclusions

We examine the impact of Chinese competition in innovation on U.S. firms' R&D and patents. We use Chinese province-level data on internet penetration and geographic industry-specific agglomeration data to generate plausibly exogenous variation in the capacity of Chinese firms to challenge U.S. firm innovation. We find that U.S. firms complain more about high competition from Chinese firms, especially in paragraphs where they discuss innovation, when industry-specific Chinese internet penetration increases. Moreover, we find direct evidence of realized ex post competition as Chinese firms apply for more patents that specifically cite the patents of the U.S. firms that are exposed to the internet penetration. In placebo tests, we find little evidence that the Chinese internet penetration impacts R&D and patenting for firms in other major economies.

We do find that Chinese import flows impact U.S. firms' patenting activity, in particular in the years right after China's admission into the WTO in 2001. However, this impact does not reduce the separate impact of competition in innovation from increased access to information via the internet.

Our main conclusion is that increased intellectual property competition has a strong and robust negative impact on U.S. firm R&D spending and realized patents. This indicates a crowding-out effect as the foreign rivals capture some of the rents of innovation. Our results vary when firms have high growth options or highly tangible assets. The impact of foreign innovation competition on U.S. firm innovation is particularly negative for firms that have higher-valued growth options as measured by their market-to-book ratios. In contrast, the impact is less severe when U.S. firms have more tangible assets and likely higher adjustment costs. As predicted by existing theories, our results are consistent with firms with trapped assets attempting to differentiate their existing products and thus investing more in R&D.

Overall our results help to reconcile disagreement in the literature on whether competition leads to increases or decreases in domestic firm innovation. Given the importance of these issues in political and regulatory circles, we believe more work examining multiple competitive margins and potential intellectual property theft would be invaluable.

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Tables

Table 1: Summary Statistics

This table shows the summary statistics of the variables used in our analyses. Detailed variable definitions can be found in Table 13

Variable	N	Mean	Std. Dev.	Median	75th	95th	99th
CNInternet	62899	0.36	0.23	0.31	0.56	0.75	0.77
# EDGARSearch$_{CN}$	52605	3.06	10.62	0.00	1.00	16.00	77.07
# EDGARSearch$_{EU}$	52605	58.23	128.17	15.00	49.00	268.00	841.00
# EDGARSearch$_{JP}$	52605	2.80	9.07	0.00	1.00	15.00	65.00
# EDGARSearch$_{NA}$	52605	32.04	61.77	11.00	31.00	142.00	396.00
CNComp % x 1000	62899	0.15	0.77	0.00	0.00	0.00	5.63
CNComp Dummy	62899	0.05	0.21	0.00	0.00	0.00	1.00
CNCompHi % x 1000	62899	0.09	0.51	0.00	0.00	0.00	3.85
CNCompHi Dummy	62899	0.03	0.18	0.00	0.00	0.00	1.00
CNIntComp % x 1000	62899	0.05	0.32	0.00	0.00	0.00	2.51
CNIntComp Dummy	62899	0.02	0.15	0.00	0.00	0.00	1.00
CNIntTheft % x 1000	62899	0.02	0.26	0.00	0.00	0.00	0.00
CNIntTheft Dummy	62899	0.01	0.10	0.00	0.00	0.00	0.00
EUComp % x 1000	62899	0.26	1.13	0.00	0.00	1.96	5.62
EUCompHi % x 1000	62899	0.14	0.78	0.00	0.00	0.00	3.83
EUIntComp % x 1000	62899	0.11	0.66	0.00	0.00	0.00	3.28
JPComp % x 1000	62899	0.04	0.26	0.00	0.00	0.00	2.18
JPCompHi % x 1000	62899	0.01	0.07	0.00	0.00	0.00	0.69
JPIntComp % x 1000	62899	0.02	0.31	0.00	0.00	0.00	0.00
NAComp % x 1000	62899	0.24	0.93	0.00	0.00	1.96	6.15
NACompHi % x 1000	62899	0.10	0.53	0.00	0.00	0.00	3.85
NAIntComp % x 1000	62899	0.05	0.32	0.00	0.00	0.00	2.53
XRD/Sales	62800	0.15	0.6	0.00	0.06	0.51	4.73
NPatent/Sales	62800	0.03	0.14	0.00	0.00	0.11	1.16
PatCiteCN	62899	3.28	35.51	0.00	0.00	5.00	66.00
PatCiteUS$_{CN}$	62899	2.36	31.85	0.00	0.00	3.00	40.00
PatCiteUS$_{EU}$	62899	26.85	237.32	0.00	1.00	57.00	549.00
PatCiteUS$_{JP}$	62899	23.88	286.82	0.00	0.00	34.00	357.71
PatCiteUS$_{NA}$	62899	5.06	53.76	0.00	0.00	11.00	93.00
PatCiteUS$_{US}$	62899	226.84	2118.64	0.00	14.00	499.00	4558.55
Age	61884	17.87	13.52	14.00	24.00	47.00	53.00
CNSalesGR	62899	0.09	0.29	0.09	0.27	0.57	0.86
log(TA)	61790	6.13	2.16	6.15	7.62	9.8	11.42
Industry Q	61831	1.95	1.78	1.36	2.09	5.03	11.19
TNIC	62899	7.56	16.25	0.96	5.04	54.32	75.24
AssetTangibility	59483	0.16	0.20	0.07	0.22	0.62	0.92

Table 2: Summary Statistics at the firm level

We first calculate the mean value of each variables for each firm, and the table shows the summary statistics of the firm-averages. Detailed variable definitions can be found in Table 13

Variable	N	Mean	Std. Dev.	Median	75th	95th	99th
CNInternet	8584	0.34	0.19	0.33	0.48	0.7	0.76
# EDGARSearch$_{CN}$	7589	2.72	7.57	0.40	1.86	12.53	42.80
# EDGARSearch$_{EU}$	7589	48.62	85.77	19.46	50.85	199.00	472.09
# EDGARSearch$_{JP}$	7589	2.20	5.81	0.33	1.75	10.00	32.18
# EDGARSearch$_{NA}$	7589	27.49	43.37	13.12	30.00	101.76	236.72
CNComp % x 1000	8584	0.16	0.69	0.00	0.00	0.98	4.42
CNComp Dummy	8584	0.05	0.18	0.00	0.00	0.36	1.00
CNCompHi % x 1000	8584	0.09	0.44	0.00	0.00	0.48	2.70
CNCompHi Dummy	8584	0.03	0.15	0.00	0.00	0.20	1.00
CNIntComp % x 1000	8584	0.05	0.26	0.00	0.00	0.17	1.55
CNIntComp Dummy	8584	0.02	0.12	0.00	0.00	0.08	0.80
CNIntTheft % x 1000	8584	0.02	0.21	0.00	0.00	0.00	1.00
CNIntTheft Dummy	8584	0.01	0.09	0.00	0.00	0.00	0.42
EUComp % x 1000	8584	0.26	0.87	0.00	0.00	1.73	4.15
EUCompHi % x 1000	8584	0.13	0.58	0.00	0.00	0.90	2.68
EUIntComp % x 1000	8584	0.11	0.50	0.00	0.00	0.66	2.37
JPComp % x 1000	8584	0.03	0.20	0.00	0.00	0.00	1.16
JPCompHi % x 1000	8584	0.01	0.05	0.00	0.00	0.00	0.23
JPIntComp % x 1000	8584	0.02	0.23	0.00	0.00	0.00	0.85
NAComp % x 1000	8584	0.22	0.74	0.00	0.00	1.51	4.08
NACompHi % x 1000	8584	0.10	0.41	0.00	0.00	0.63	2.22
NAIntComp % x 1000	8584	0.04	0.24	0.00	0.00	0.19	1.24
XRD/Sales	8279	0.22	0.70	0.00	0.10	1.26	4.38
NPatent/Sales	8279	0.03	0.12	0.00	0.00	0.13	0.78
PatCiteCN	8584	1.76	21.20	0.00	0.00	2.16	33.55
PatCiteUS$_{CN}$	8584	1.28	18.39	0.00	0.00	1.53	21.01
PatCiteUS$_{EU}$	8584	15.33	163.61	0.00	0.50	25.99	302.83
PatCiteUS$_{JP}$	8584	13.26	192.43	0.00	0.13	15.50	190.17
PatCiteUS$_{NA}$	8584	2.87	34.20	0.00	0.00	5.00	50.26
PatCiteUS$_{US}$	8584	130.27	1476.00	0.00	5.40	225.85	2455.58
Age	8575	13.80	12.12	9.50	17.50	44.00	48.00
CNSalesGR	8584	0.09	0.15	0.07	0.14	0.35	0.47
log(TA)	8584	5.68	2.11	5.64	7.11	9.27	10.89
Industry Q	8584	1.97	1.40	1.48	2.28	4.72	7.75
TNIC	8584	7.98	15.82	1.41	6.27	51.38	71.77
AssetTangibility	8302	0.15	0.20	0.07	0.21	0.61	0.81

Table 3: EDGAR searches and Chinese internet penetration

The table displays OLS regressions in which the dependent variable is the number of EDGAR searches scaled by sales. For ease of interpretation, we standardize this variable to have unit variance in each year. Column (1) tabulates EDGAR searches whose IP addresses are from China; Column (2) tabulates European IP addresses, Column (3) counts Japanese IP addresses, and Column (4) counts Canadian and Mexican IP addresses. Following Lee, Ma, and Wang (2015), we exclude EDGAR searches by web crawlers. In Panel A, the internet penetration variable is constructed using the weights from all Chinese-domiciled public firms listed in mainland China, Hong Kong, and the U.S. In Panel B, the internet penetration variable is constructed using the weights from the subset of these firms that are listed only via mainland China A-shares. All RHS variables are also standardized to have unit variance for ease of interpretation. The sample includes all Compustat firms from 2004 to 2015 with available 10K filings on the EDGAR system as the EDGAR server log starts in February of 2003. We exclude all observations where the total assets or sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Weights from A-share, HK-, and US-listed firms

	# of EDGAR searches / Sales			
	CN	EU	JP	NA
	(1)	(2)	(3)	(4)
CNInternet	0.099**	−0.003	0.063	0.016
	(0.047)	(0.046)	(0.047)	(0.044)
CNSalesGR	−0.007	−0.001	−0.004	0.006
	(0.004)	(0.004)	(0.005)	(0.005)
log(10kSize)	0.013*	0.014**	0.010	0.016***
	(0.007)	(0.006)	(0.007)	(0.006)
log(Age + 1)	0.131***	0.135***	0.095***	0.073***
	(0.029)	(0.024)	(0.024)	(0.026)
log(TA)	−0.229***	−0.434***	−0.203***	−0.420***
	(0.041)	(0.044)	(0.041)	(0.044)
Industry Q	0.001	0.009	−0.018	0.021
	(0.013)	(0.016)	(0.018)	(0.017)
TNIC	0.013	0.011	0.015	0.018**
	(0.012)	(0.011)	(0.012)	(0.009)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	48,808	48,808	48,808	48,808

Panel B: Weights from A-share firms only

	# of EDGAR searches / Sales			
	CN	EU	JP	NA
	(1)	(2)	(3)	(4)
CNInternet	0.112***	−0.019	0.051	−0.00002
	(0.043)	(0.048)	(0.044)	(0.043)
CNSalesGR	−0.007	−0.001	−0.004	0.006
	(0.004)	(0.004)	(0.005)	(0.005)
log(10kSize)	0.013*	0.014**	0.010	0.016***
	(0.007)	(0.006)	(0.007)	(0.006)
log(Age + 1)	0.131***	0.135***	0.095***	0.073***
	(0.029)	(0.024)	(0.024)	(0.026)
log(TA)	−0.228***	−0.434***	−0.203***	−0.420***
	(0.041)	(0.044)	(0.041)	(0.044)
Industry Q	0.001	0.009	−0.018	0.021
	(0.013)	(0.016)	(0.018)	(0.017)
TNIC	0.013	0.012	0.015	0.018**
	(0.012)	(0.011)	(0.012)	(0.009)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	48,808	48,808	48,808	48,808

Table 4: Competition complaints and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are textual measures of competition complaints in 10K filings. We search for four types of complaints in the 10K filings. CNComp measures competition in general; CNCompHi measures competition with high intensity; CNIntComp measures intellectual property competition; CNIntTheft measures intellectual property theft. All these competition measures are China-specific, meaning the words "China" or "Chinese" appear in the the same paragraph as the competition complaint phrases. We exclude instances if other countries are in the same paragraph to ensure the compeitition disucssion is truely about China. More detailed variable construction procedures can be found in Table 13 in the Appendix. In Columns (1), (3), (5), and (7), the dependent variables are the number of paragraphs containing the above search instances divided by the total number of paragraphs of the 10K filing. In Columns (2), (4), (6), and (8), the dependent variables are dummies that equal to 1 if we found any of the phrases in the search. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables, except for *log(10kSize)*, are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2001 to 2015 with 10K filings. We exclude all observations where the total asset or sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp		CNCompHi		CNIntComp		CNIntTheft	
	%	dummy	%	dummy	%	dummy	%	dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CNInternet	0.122***	0.155***	0.118***	0.137***	0.126***	0.148***	0.081**	0.102***
	(0.041)	(0.044)	(0.039)	(0.042)	(0.040)	(0.041)	(0.041)	(0.038)
CNSalesGR	0.001	0.006*	−0.001	0.002	−0.001	0.001	−0.002	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(10kSize)	−0.106***	−0.031***	−0.110***	−0.051***	−0.097***	−0.062***	−0.069***	−0.027***
	(0.010)	(0.008)	(0.011)	(0.009)	(0.011)	(0.010)	(0.014)	(0.009)
log(Age + 1)	−0.053**	−0.051**	−0.057**	−0.053**	−0.026	−0.023	−0.020	−0.018
	(0.022)	(0.023)	(0.023)	(0.023)	(0.025)	(0.025)	(0.026)	(0.023)
log(TA)	0.045	0.028	0.058**	0.040	0.033	0.026	0.075***	0.068***
	(0.028)	(0.027)	(0.027)	(0.026)	(0.031)	(0.029)	(0.028)	(0.025)
Industry Q	−0.018***	−0.016***	−0.016***	−0.015***	−0.021***	−0.020***	−0.021***	−0.011
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)
TNIC	−0.003	−0.004	−0.003	−0.007	−0.012**	−0.013**	−0.006	−0.010*
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,899	62,899	62,899	62,899	62,899

Table 5: Placebo tests - Competition from other countries and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are textual measures of competition complaints from 10K filings. The dependent variables are constructed in a similar way as in Table 4. However, instead of measuring China-related competition complaints, we now search for competition complaints about other regions of the world. More specifically, Columns (1) - (2) report searches using European Union countries, Column (3) - (4) using Japan, and Columns (5)-(6) using Canada and Mexico. All the dependent variables are the count of matched paragraphs divided by the total number of paragraphs in the 10K filings. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables, except for *log(10kSize)*, are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2001 to 2015 with 10K filings. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Weights from A-share, HK-, and US-listed firms

	JP		NA		EU	
	IntComp	IntTheft	IntComp	IntTheft	IntComp	IntTheft
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	0.020	−0.010	0.050	0.000	0.085*	0.035
	(0.035)	(0.012)	(0.043)	(0.000)	(0.047)	(0.024)
CNSalesGR	−0.001	−0.001	0.0001	0.000	−0.0005	−0.001
	(0.003)	(0.001)	(0.004)	(0.000)	(0.003)	(0.001)
log(10kSize)	−0.078***	−0.011***	−0.149***	0.000	−0.208***	−0.063***
	(0.014)	(0.003)	(0.014)	(0.000)	(0.018)	(0.008)
log(Age + 1)	0.035**	0.012**	−0.041	0.000	−0.047**	−0.006
	(0.017)	(0.005)	(0.025)	(0.000)	(0.023)	(0.012)
log(TA)	0.062*	0.009	0.131***	0.000	0.202***	0.088***
	(0.034)	(0.008)	(0.031)	(0.000)	(0.039)	(0.021)
Industry Q	0.008	0.003	0.010	0.000	−0.016	0.005
	(0.009)	(0.003)	(0.008)	(0.000)	(0.011)	(0.008)
TNIC	−0.002	−0.002	0.002	0.000	0.008	0.003
	(0.006)	(0.002)	(0.008)	(0.000)	(0.009)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,899	62,899	62,899

Panel B: Weights from A-share listed firms only

	JP		NA		EU	
	IntComp	IntTheft	IntComp	IntTheft	IntComp	IntTheft
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	0.013	−0.014	0.052	0.000	0.042	0.009
	(0.033)	(0.011)	(0.038)	(0.000)	(0.048)	(0.023)
CNSalesGR	−0.001	−0.001	0.00000	0.000	−0.001	−0.001
	(0.003)	(0.001)	(0.004)	(0.000)	(0.003)	(0.001)
log(10kSize)	−0.078***	−0.011***	−0.149***	0.000	−0.208***	−0.063***
	(0.014)	(0.003)	(0.014)	(0.000)	(0.018)	(0.008)
log(Age + 1)	0.035**	0.011**	−0.040	0.000	−0.047**	−0.006
	(0.017)	(0.005)	(0.025)	(0.000)	(0.022)	(0.012)
log(TA)	0.062*	0.009	0.132***	0.000	0.202***	0.088***
	(0.034)	(0.008)	(0.031)	(0.000)	(0.039)	(0.021)
Industry Q	0.008	0.003	0.009	0.000	−0.017	0.005
	(0.009)	(0.003)	(0.008)	(0.000)	(0.011)	(0.008)
TNIC	−0.002	−0.002	0.002	0.000	0.009	0.004
	(0.006)	(0.002)	(0.008)	(0.000)	(0.009)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,899	62,899	62,899

Table 6: Innovation activities and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are firms' innovation activities. The dependent variable in Columns (1) - (3) is the R&D expenses over sales. For missing R&D, we follow the Koh and Reeb (2015) and replace the missing with industry average if the firm files for any patent patents applications in the past three years (including the current year), and 0 otherwise. The dependent variables are measures from 1, 2, or 3 years in the future. Note all the variables are normalized by the sales from year t. The dependent variable in Columns (4) - (6) is the total number of patent applications each year (by filing date) divided by sales. The patent data comes from Google Patents, and we match the patents to Compustat firms using the links from Kogan, Papanikolaou, Seru, and Stoffman (2016). The dependent variables are measures from 1, 2, or 3 years in the future. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2003 to 2015. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	XRD/Sales			NPatent / Sales		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	−0.188***	−0.222***	−0.240***	−0.105***	−0.099***	−0.104***
	(0.041)	(0.043)	(0.045)	(0.041)	(0.037)	(0.036)
CNSalesGR	0.005**	0.003	0.003	−0.001	0.005***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Age + 1)	−0.113***	−0.110***	−0.102***	−0.091***	−0.102***	−0.094***
	(0.016)	(0.017)	(0.019)	(0.018)	(0.017)	(0.018)
log(TA)	0.032	−0.011	−0.109***	−0.066**	−0.086***	−0.114***
	(0.028)	(0.030)	(0.033)	(0.029)	(0.028)	(0.027)
Industry Q	0.040***	0.054***	0.049***	0.028**	0.009	0.003
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
TNIC	0.039***	0.041***	0.038***	0.020**	0.031***	0.029***
	(0.010)	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	62,800	54,696	47,478	62,800	54,696	47,478

Table 7: Competition in Innovation vs. Existing Products

This table compares the competition in innovation with the product market competition. Panel A shows our main tests. The key new independent variable, CNImport, is the import penetration ratio from China, defined for each 3-digit SIC industries. The dependent variables in Columns (1)-(4) are the R&D expenses divided by the sales in the previous year, and the dependent variables in Columns (5)-(8) are the number of patents dividend by the sales in the previous years. Columns (1)-(3) and (5)-(7) include observations from 2001-2007, and Columns (4) and (8) use the full sample period (2001-2016) from our paper. The sample construction follows the same procedure as in previous tables. We exclude all observations where the total asset or the sales are smaller than one million dollars. In Panel B, we test the effects of only CNImport on innovation activities. The dependent variables are the same as in Panel A. Columns (1), and (3) use observations from 1997-2007, while the other column use the full sample in our paper (2001-2016). All independent variables are one-year lagged relative to the dependent variables, and all the variables are normalized by their standard deviations for easier interpretation. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Competition in Innovation vs. Existing Products

	XRD/Sales				NPatents/Sales			
	2001-2007			01-16	2001-2007			01-16
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CNInternet	−0.174**		−0.176*	−0.198***	−0.120		−0.101	−0.103**
	(0.085)		(0.094)	(0.044)	(0.091)		(0.098)	(0.042)
CNImport		−0.014	−0.006	0.010		−0.035**	−0.031*	−0.004
		(0.012)	(0.014)	(0.007)		(0.017)	(0.018)	(0.014)
CNSalesGR	0.004	0.004	0.004	0.005**	0.001	−0.00004	0.0004	−0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
log(Age + 1)	−0.153***	−0.154***	−0.155***	−0.114***	−0.147***	−0.149***	−0.150***	−0.093***
	(0.031)	(0.031)	(0.031)	(0.016)	(0.033)	(0.033)	(0.033)	(0.018)
log(TA)	0.105***	0.106***	0.104***	0.033	−0.014	−0.019	−0.020	−0.067**
	(0.038)	(0.039)	(0.038)	(0.028)	(0.041)	(0.042)	(0.042)	(0.029)
Industry Q	0.039***	0.039***	0.039***	0.041***	0.034**	0.034**	0.033**	0.028**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)	(0.013)
TNIC	0.052***	0.050***	0.052***	0.040***	0.035***	0.033**	0.034***	0.020**
	(0.014)	(0.014)	(0.014)	(0.010)	(0.013)	(0.013)	(0.013)	(0.008)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	32,818	32,590	32,590	62,309	32,818	32,590	32,590	62,309

Panel B: Competition in Existing Products

	XRD/Sales		NPatents/Sales	
	1997-2007	2001 - 2016	1997-2007	2001 - 2016
	(1)	(2)	(3)	(4)
CNImport	−0.035***	−0.015**	−0.027*	−0.022*
	(0.012)	(0.007)	(0.014)	(0.012)
Size	−0.233***	−0.031	−0.145***	−0.065**
	(0.036)	(0.026)	(0.042)	(0.027)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	46,198	74,330	46,198	74,330

Table 8: Innovation activities and Chinese internet penetration - Poisson Regression

The table displays poisson regressions in which the dependent variables are firms' innovation activities. The dependent variable in Columns (1) - (3) is the R&D expenses over sales. For missing R&D, we follow the Koh and Reeb (2015) and replace the missing with industry average if the firm files for any patent patents applications in the past three years (including the current year), and 0 otherwise. The dependent variables are measures from 1, 2, or 3 years in the future. The dependent variable in Columns (4) - (6) is the total number of patent applications each year (by filing date) dividend by sales. The patent data comes from Google Patents, and we match the patents to Compustat firms using the links from Kogan, Papanikolaou, Seru, and Stoffman (2016). The dependent variables are measures from 1, 2, or 3 years in the future. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2003 to 2015. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	XRD/Sales			NPatent / Sales		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	-0.382***	-0.493***	-0.465***	-0.413***	-0.456***	-0.544***
	(0.055)	(0.074)	(0.061)	(0.111)	(0.127)	(0.116)
CNSalesGR	-0.031**	-0.023	-0.048***	-0.053***	-0.005	-0.058***
	(0.014)	(0.018)	(0.015)	(0.020)	(0.019)	(0.018)
log(Age + 1)	-0.199***	-0.224***	-0.127***	0.003	-0.060	-0.019
	(0.017)	(0.022)	(0.018)	(0.034)	(0.038)	(0.032)
log(AT)	-0.506***	-0.614***	-0.583***	-0.378***	-0.420***	-0.421***
	(0.026)	(0.029)	(0.024)	(0.037)	(0.037)	(0.036)
Industry Q	0.093***	0.122***	0.084***	0.025	0.087***	0.061***
	(0.016)	(0.019)	(0.018)	(0.018)	(0.023)	(0.021)
TNIC	0.103***	0.206***	0.076***	0.013	0.109**	0.060
	(0.021)	(0.033)	(0.025)	(0.041)	(0.046)	(0.042)
Lagged XRD/Sales	0.642***	0.224***	0.322***			
	(0.040)	(0.023)	(0.022)			
Lagged NPatent/Sales				1.643***	0.221***	0.255***
				(0.162)	(0.023)	(0.024)
Year FE	Y	Y	Y	Y	Y	Y
N	62,800	54,696	47,478	62,800	54,696	47,478

Table 9: Patent citations and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are the annual number of citations by Chinese firms on the firm's existing patents. In Columns (1) - (3), for each firm we count the number of new patents that have cited the firm's existing patents in each year. We further require the first assignee of the citing patent is a Chinese company, and the patent is filed in the US with USPTO. The dependent variables in Columns (1) - (3) are the total count number, PatCiteUS$_{CN}$, divided by sales in the next three years, respectively. In Columns (4) - (6), we further compare PatCiteUS$_{CN}$ to the number of citations from news patents which are filed with USPTO and assigned to US firms. The dependent variables in Columns (4) - (6) are PatCiteUS$_{CN}$/(PatCiteUS$_{CN}$ + PatCiteUS$_{US}$ + 1) in the next three years, respectively. In Columns (7) - (9), PatCiteCN counts the number of new patents filed with Chinese Patent Office (SIPO) that have cited the firm's existing patents. We exclude patents that are filed in SIPO but are assigned to US companies. In Columns (10) - (12), we use PatCiteCN / (PatCiteCN + PatCiteUS + 1) as the dependent variables, where the PatCiteUS is the total counts of new citing patents filed in the US. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2003 to 2015. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	$\frac{PatCiteUS_{CN}}{Sales}$			$\frac{PatCiteUS_{CN}}{PatCiteUS_{CN}+PatCiteUS_{US}+1}$			$\frac{PatCiteCN}{Sales}$			$\frac{PatCiteCN}{PatCiteCN+PatCiteUS+1}$		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CNInternet	0.288***	0.212***	0.160***	0.263***	0.261***	0.220***	0.250***	0.153***	0.113**	0.332***	0.289***	0.291***
	(0.052)	(0.050)	(0.053)	(0.045)	(0.045)	(0.047)	(0.045)	(0.042)	(0.045)	(0.047)	(0.051)	(0.055)
CNSalesGR	−0.0005	0.004	0.007*	0.001	0.006	0.015***	0.001	0.008**	0.011***	−0.007*	0.002	0.011**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
log(Age + 1)	0.052**	0.060***	0.024	−0.063***	−0.049**	−0.032	−0.003	0.007	0.006	−0.425***	−0.405***	−0.386***
	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)	(0.022)	(0.018)	(0.018)	(0.019)	(0.027)	(0.028)	(0.028)
log(TA)	−0.280***	−0.260***	−0.202***	−0.106***	−0.091***	−0.080***	−0.327***	−0.319***	−0.286***	−0.023	−0.044	−0.047
	(0.033)	(0.035)	(0.035)	(0.026)	(0.028)	(0.030)	(0.033)	(0.035)	(0.038)	(0.028)	(0.029)	(0.031)
Industry Q	−0.051***	−0.039***	−0.045***	−0.043***	−0.041***	−0.035***	−0.024**	−0.028**	−0.020	0.0003	−0.003	−0.0004
	(0.012)	(0.013)	(0.014)	(0.008)	(0.009)	(0.010)	(0.012)	(0.011)	(0.013)	(0.007)	(0.008)	(0.008)
TNIC	−0.025***	−0.012	−0.004	−0.012	−0.004	−0.007	−0.0004	−0.004	−0.008	0.016**	0.016**	0.018**
	(0.009)	(0.009)	(0.010)	(0.007)	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	62,832	54,696	47,478	62,832	54,763	47,584	62,832	54,696	47,478	62,832	54,763	47,584

Table 10: Placebo tests - patent citations from other counties and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are the annual number of citations by firms in other economies on the firm's existing patents. We define the dependent variables as in the Columns (1)-(3) of Table 9. PatCiteUS$_{it}^{JP}$ are the number of patents, which are filed by Japanese firms with USPTO in year t, that cite firm i's existing patents. Similarly, PatCiteUS$_{it}^{NA}$ are the patent counts filed by firms from Canada or Mexica, and PatCiteUS$_{it}^{EU}$, the firms from European Union. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2003 to 2015. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	$\frac{PatCiteUS_{JP}}{Sales}$			$\frac{PatCiteUS_{NA}}{Sales}$			$\frac{PatCiteUS_{EU}}{Sales}$		
	t+1	t+2	t+3	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CNInternet	−0.038	−0.065	−0.070	0.029	0.055	0.041	−0.010	−0.042	−0.040
	(0.043)	(0.045)	(0.048)	(0.043)	(0.042)	(0.045)	(0.044)	(0.044)	(0.047)
CNSalesGR	−0.001	0.005**	−0.003	−0.005*	0.002	−0.002	−0.0003	0.002	−0.00001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
log(Age + 1)	0.070***	0.034**	0.027	0.077***	0.064***	0.057***	0.066***	0.011	0.027
	(0.016)	(0.017)	(0.019)	(0.017)	(0.018)	(0.019)	(0.015)	(0.017)	(0.017)
log(TA)	−0.188***	−0.187***	−0.030	−0.207***	−0.214***	−0.100***	−0.193***	−0.167***	−0.056*
	(0.029)	(0.033)	(0.035)	(0.029)	(0.032)	(0.030)	(0.030)	(0.031)	(0.032)
Industry Q	−0.028**	0.005	−0.005	−0.022	0.001	−0.003	−0.026**	0.009	−0.003
	(0.011)	(0.012)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)	(0.013)	(0.013)
TNIC	0.016**	0.025***	0.002	−0.015*	−0.008	−0.013	0.001	0.024***	−0.0002
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	62,832	54,696	47,584	62,832	54,696	47,584	62,832	54,696	47,584

Table 11: Subsample analysis - by Q

This table re-estimates regressions in Table 4 and 6 with an additional variable, HighQ, which equals to 1 if a firm's Q is higher than the median Q in each year, and 0 otherwise. We interact the HighQ dummy with the Chinese internet penetration variable and test whether high- and low-Q firms have different reponses in their innovation activities to Chinese competition. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample construction follows the same procedure as in previous tables. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp	CNCompHi	CNIntComp	XRD/Sales		NPatent/Sales	
	t+1	t+1	t+1	t+1	t+3	t+1	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CNInternet x HighQ	0.030**	0.027**	0.026*	−0.062***	−0.065***	−0.045***	−0.059***
	(0.012)	(0.013)	(0.013)	(0.010)	(0.013)	(0.011)	(0.012)
CNInternet	0.103**	0.101**	0.110***	−0.152***	−0.208***	−0.080**	−0.074**
	(0.042)	(0.040)	(0.040)	(0.037)	(0.041)	(0.038)	(0.033)
CNSalesGR x HighQ	−0.003	−0.004	−0.001	0.006*	−0.004	−0.0002	0.006*
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
CNSalesGR	0.002	0.001	−0.001	0.002	0.005**	−0.0004	−0.0003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
HighQ	−0.043**	−0.047**	−0.059***	0.081***	0.067***	0.022	0.060***
	(0.019)	(0.020)	(0.020)	(0.019)	(0.021)	(0.020)	(0.020)
log(10kSize)	−0.106***	−0.109***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.053**	−0.057**	−0.027	−0.116***	−0.104***	−0.094***	−0.097***
	(0.022)	(0.023)	(0.025)	(0.016)	(0.019)	(0.018)	(0.018)
log(TA)	0.042	0.055**	0.028	0.039	−0.103***	−0.064**	−0.109***
	(0.028)	(0.027)	(0.031)	(0.027)	(0.033)	(0.029)	(0.027)
Industry Q	−0.016***	−0.013**	−0.016**	0.037***	0.048***	0.034**	0.001
	(0.005)	(0.005)	(0.006)	(0.014)	(0.014)	(0.014)	(0.014)
TNIC	−0.001	−0.002	−0.011*	0.036***	0.035***	0.017**	0.026***
	(0.005)	(0.005)	(0.006)	(0.010)	(0.011)	(0.008)	(0.008)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,800	47,478	62,800	47,478

Table 12: Subsample analysis - by Asset Tangibility

This table re-estimates regressions in Table 4 and 6 with an additional variable, HighT, which equals to 1 if a firm's asset tangibility is higher than the median asset tangibility in each year, and 0 otherwise. We interact the HighT dummy with the Chinese internet penetration variable and test whether high- and low-asset tangibility firms have different reponses in their innovation activities to Chinese competition. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample construction follows the same procedure as in previous tables. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp	CNCompHi	CNIntComp	XRD/Sales		NPatent/Sales	
	t+1	t+1	t+1	t+1	t+3	t+1	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CNInternet x HighT	0.032**	0.026*	0.039**	0.065***	0.060***	0.046***	0.054***
	(0.014)	(0.015)	(0.016)	(0.013)	(0.015)	(0.013)	(0.013)
CNInternet	0.096**	0.097**	0.095**	−0.232***	−0.283***	−0.137***	−0.135***
	(0.044)	(0.043)	(0.042)	(0.049)	(0.054)	(0.048)	(0.042)
CNSalesGR x HighT	0.005	0.005	0.005	−0.003	0.002	0.004	0.001
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
CNSalesGR	−0.002	−0.004	−0.004	0.007*	0.002	−0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
HighT	−0.003	0.001	0.014	−0.104***	−0.114***	−0.046*	−0.075***
	(0.024)	(0.024)	(0.027)	(0.023)	(0.026)	(0.027)	(0.025)
log(10kSize)	−0.112***	−0.115***	−0.101***				
	(0.011)	(0.012)	(0.012)				
log(Age + 1)	−0.047*	−0.053**	−0.018	−0.115***	−0.103***	−0.104***	−0.100***
	(0.026)	(0.027)	(0.029)	(0.019)	(0.022)	(0.021)	(0.021)
log(TA)	0.049*	0.066**	0.040	0.033	−0.114***	−0.071**	−0.121***
	(0.030)	(0.029)	(0.033)	(0.029)	(0.035)	(0.031)	(0.029)
Industry Q	−0.015***	−0.013**	−0.016**	0.036***	0.042***	0.028**	−0.001
	(0.006)	(0.006)	(0.007)	(0.014)	(0.014)	(0.014)	(0.013)
TNIC	−0.003	−0.003	−0.012*	0.044***	0.042***	0.022**	0.032***
	(0.006)	(0.005)	(0.006)	(0.011)	(0.012)	(0.009)	(0.009)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	59,640	59,640	59,640	59,411	44,837	59,411	44,837

Figures

Figure 1: Complaints about Chinese competition

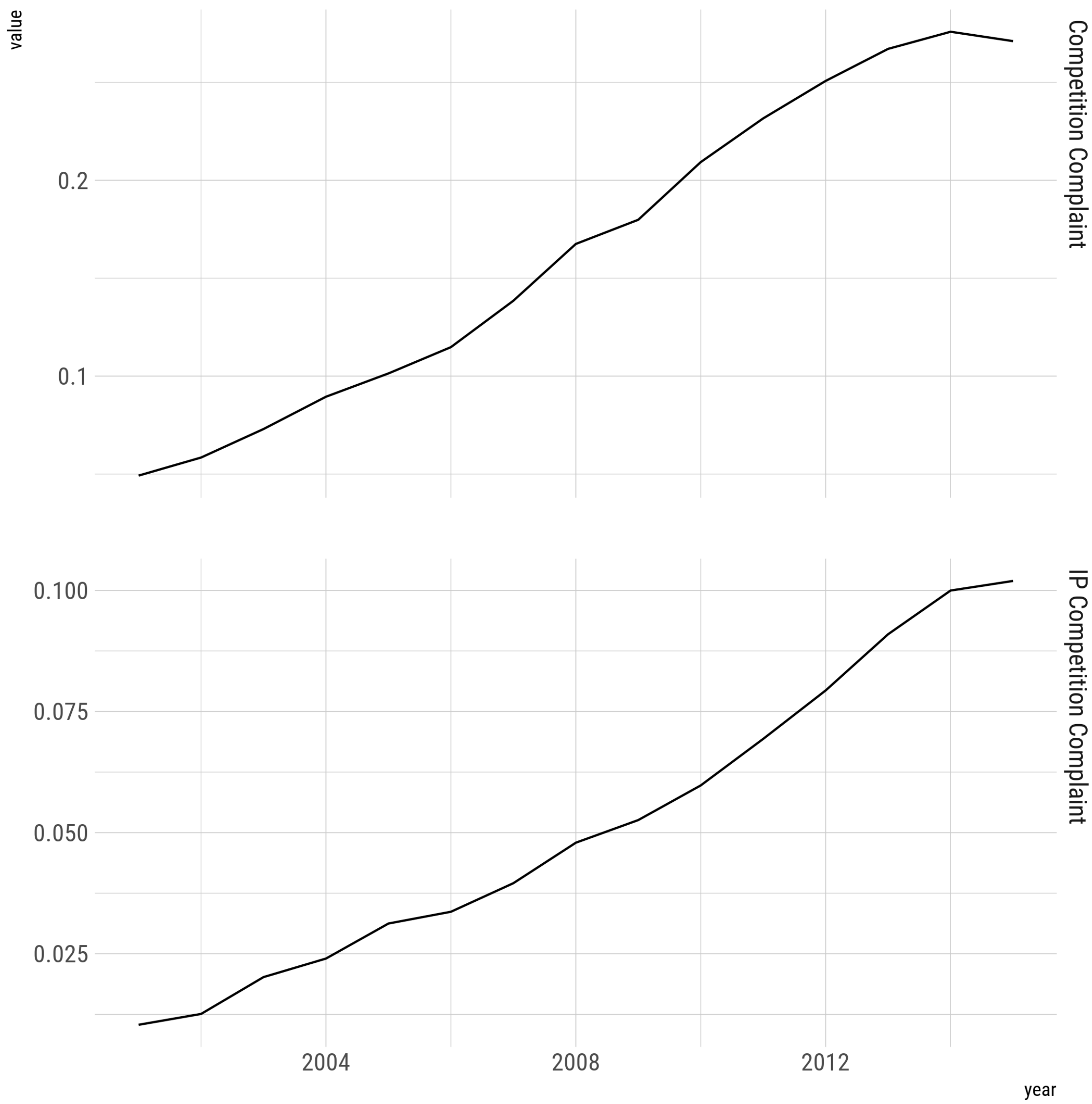


Figure 2: Internet penetration growth variation

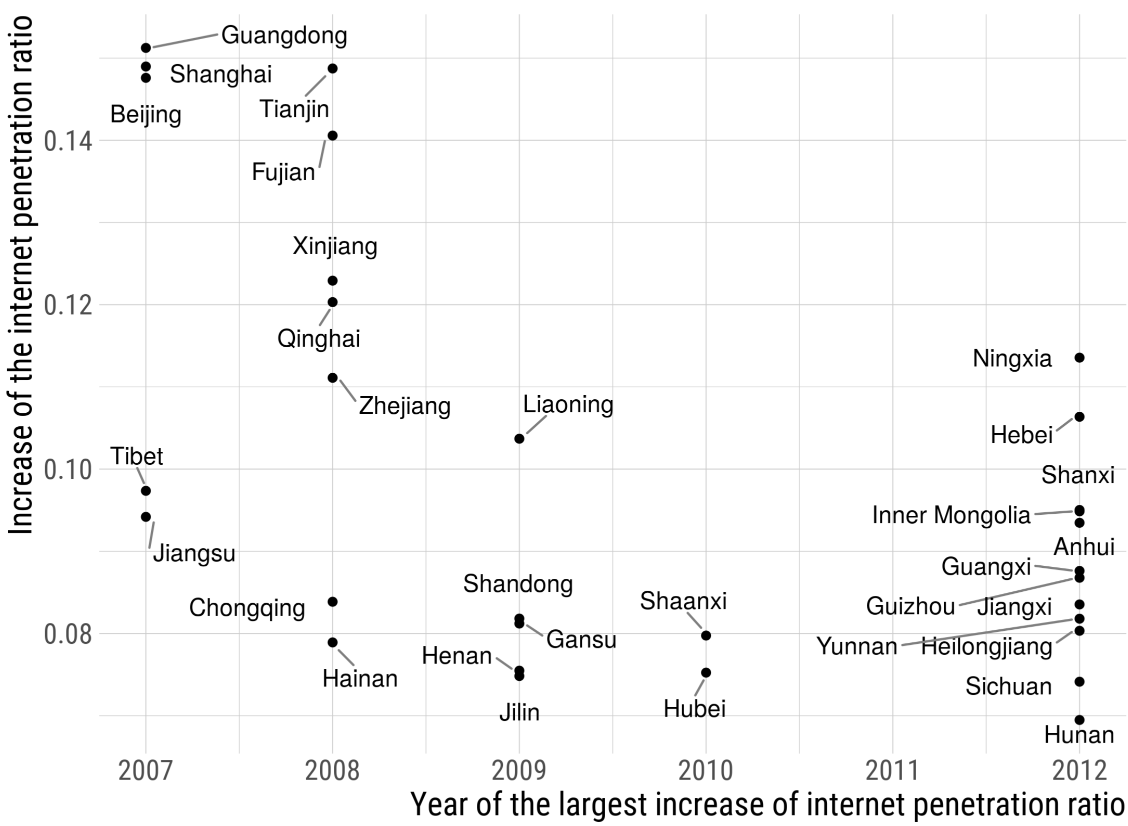


Figure 3: Number of industries (SIC2) covered by Chinese public firms

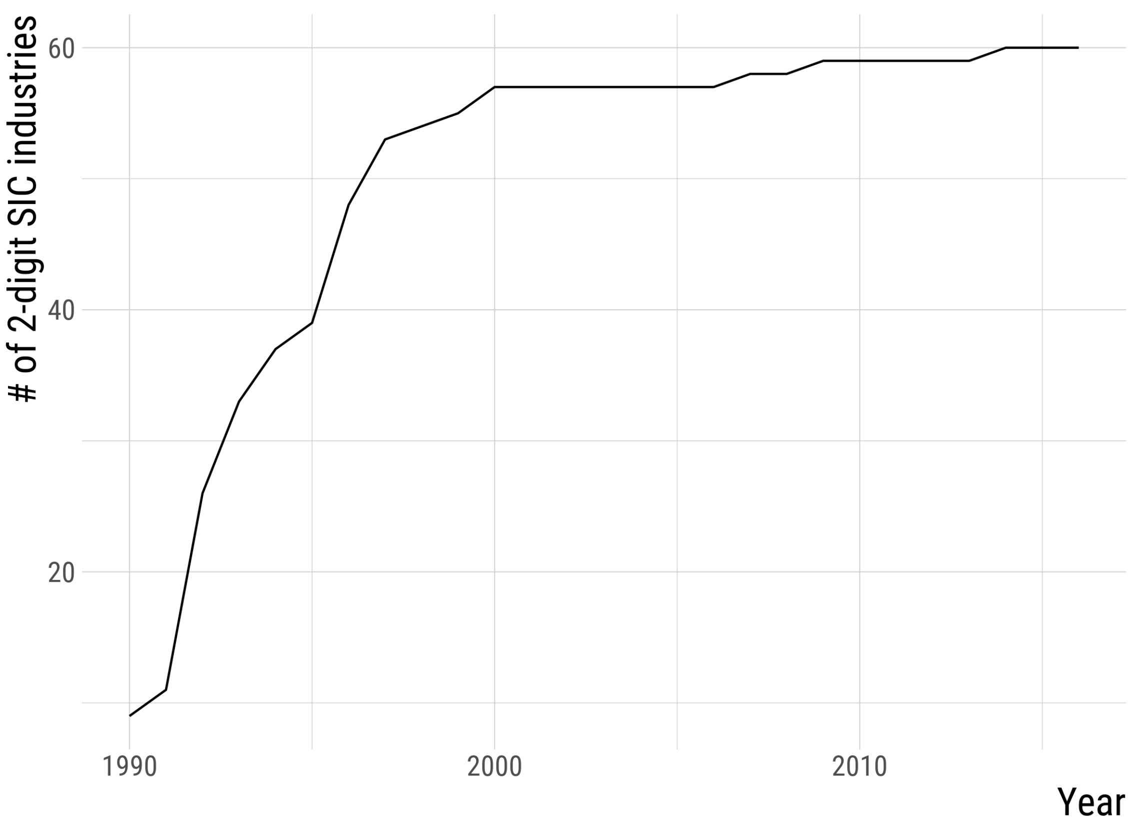
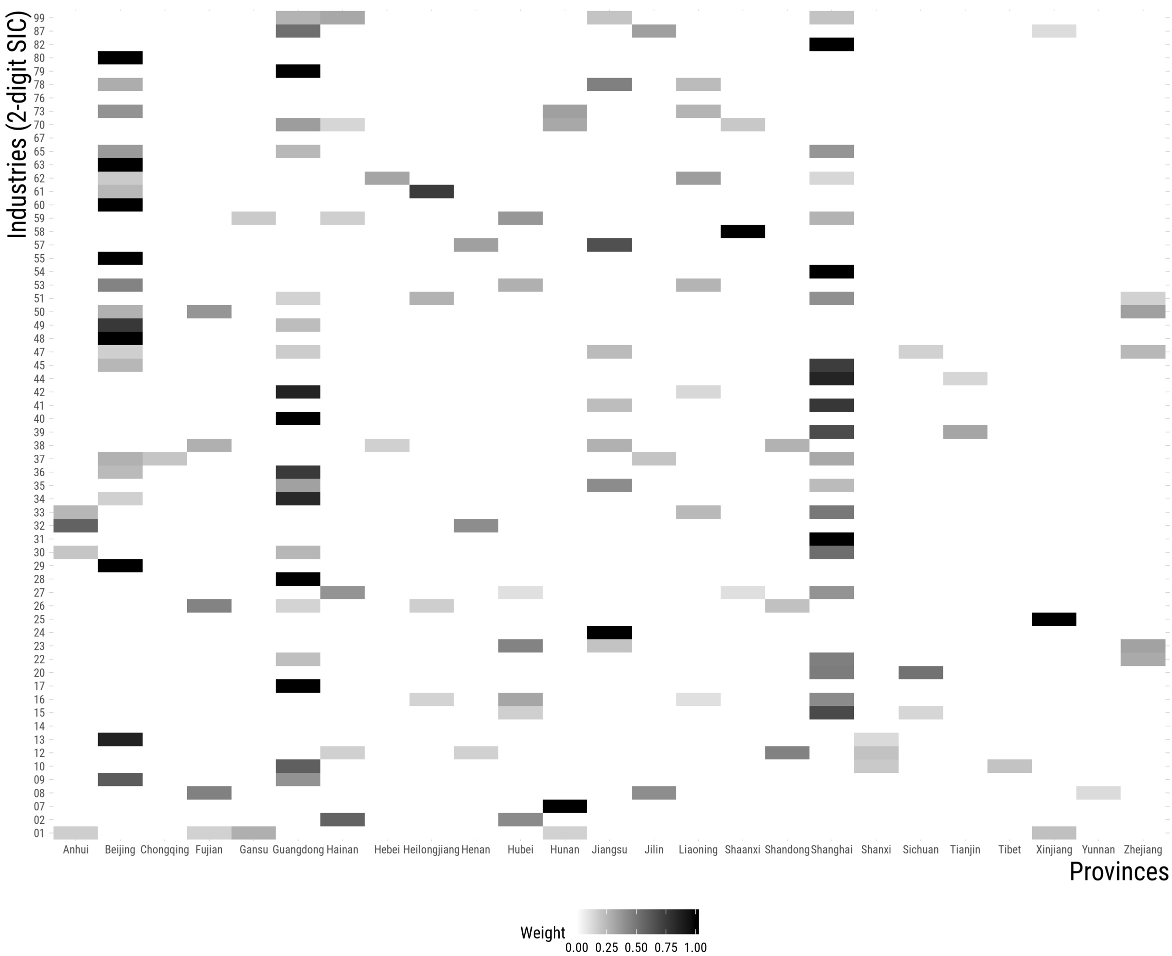


Figure 4: Weight loadings by Province-Industry



Appendix A. Variable definitions

Table 13: Variable definitions

Table 13

Variable	Definition	Source
CNInternet	The weighted average internet penetration ratio across provinces in China. We first collect the number of internet users from annual reports. We then get the number of population for each province-year from China Data Online and calculate the internet penetration ratio. Next, for each industry, we calculate the weights across provinces using the total assets of all the Chinese public firms (mainland A-share, Hongkong, and US) in 2000, and the same weights are used in all later years. We assign each public firm to the province of its headquarter. In calculating the weights for each industry, we keep only provinces whose weights are above 10%, and then calculate CNInternet as the weighted-average of the internet penetration ratio, where the weights are the total asset of the public firms of the industry from the province.	CNNIC Reports; CSMAR; Capital IQ; China Data Online
CNComp %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [China, Chinese]; List 2: [compete, competition, competing]	10-K Filing
CNComp Dummy	A dummy variable that equals to one if CNComp % is larger than 0, and 0 otherwise.	10-K Filing
CNCompHi %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [China, Chinese]; List 2: [compete, competition, competing]; List 3: [high, intense, significant, face, faces, substantial, significant, continued, vigorous, strong, aggressive, fierce, stiff, extensive, severe]	10-K Filing
CNCompHi Dummy	A dummy variable that equals to one if CNCompHi % is larger than 0, and 0 otherwise.	10-K Filing
CNIntComp %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [China, Chinese]; List 2: [compete, competition, competing]; List 3: [intellectual]; List 4: [property]	10-K Filing
CNIntComp Dummy	A dummy variable that equals to one if CNIntComp % is larger than 0, and 0 otherwise.	10-K Filing
CNIntTheft %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [China, Chinese]; List 2: [infringe, theft, steal, stolen]; List 3: [intellectual property, trade secret]	10-K Filing
CNIntTheft Dummy	A dummy variable that equals to one if CNIntTheft % is larger than 0, and 0 otherwise.	10-K Filing
EUIntComp %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Europe, European]; List 2: [compete, competition, competing]; List 3: [intellectual]; List 4: [property]	10-K Filing
EUIntTheft %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Europe, European]; List 2: [infringe, theft, steal, stolen]; List 3: [intellectual property, trade secret]	10-K Filing
JPIntComp %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Japan, Japanese]; List 2: [compete, competition, competing]; List 3: [intellectual]; List 4: [property]	10-K Filing

Continued on next page

Table 13 – *Continued from previous page*

Variable	Definition	Source
JPIntTheft %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Japan, Japanese]; List 2: [infringe, theft, steal, stolen]; List 3: [intellectual property, trade secret]	10-K Filing
NAIntComp %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Mexico, Mexican, Canada, Canadian]; List 2: [compete, competition, competing]; List 3: [intellectual]; List 4: [property]	10-K Filing
NAIntTheft %	# of paragraphs that contain at least one words from the following word lists divided by the total number of paragraphs of the 10-K filing. List 1: [Mexico, Mexican, Canada, Canadian]; [infringe, theft, steal, stolen]; List 3: [intellectual property, trade secret]	10-K Filing
XRD	R&D expenses from Compustat. We replace the missing R&D expense ratio (over sales) by the industry average if the firms has applied for any patents in the past three years. We replace the other missing variables with 0.	Compustat
NPatent	The number of patents that the firm applies in a year. For patents granted prior to Nov. 1, 2010, we use the KPSS data; For patents granted after Nov. 1, 2010, we use the patent data from Google patents.	Google Patent; Kogan, Papanikolaou, Seru, and Stoffman (2016)
PatCiteCN	The total number of new patents that (1) are applied in SIPO (China Patent Office), (2) assigned to a Chinese firm, and (3) cite any existing patents of the firm	Google Patent
PatCiteUS$_{CN}$	The total number of new patents that (1) are applied in USPTO, (2) assigned to a Chinese firm, and (3) cite any existing patents of the firm	Google Patent
PatCiteUS$_{EU}$	The total number of new patents that (1) are applied in USPTO, (2) assigned to an European firm, and (3) cite any existing patents of the firm	Google Patent
PatCiteUS$_{JP}$	The total number of new patents that (1) are applied in USPTO, (2) assigned to a Japanese firm, and (3) cite any existing patents of the firm	Google Patent
PatCiteUS$_{NA}$	The total number of new patents that (1) are applied in USPTO, (2) assigned to a Mexican or Canadian firm, and (3) cite any existing patents of the firm	Google Patent
PatCiteUS$_{US}$	The total number of new patents that (1) are applied in USPTO, (2) assigned to an American firm, and (3) cite any existing patents of the firm	Google Patent
Age	Number of years that the firm has been public	Compustat
CNSalesGR	The average sales growth of the Chinese public company of the same 2-digit SIC industry	CSMAR; Capital IQ
Industry Q	Weighted average of peer firms' market-to-book ratios. The weights are the similarity scores from the TNIC network	Compustat; Hoberg and Phillips (2016)
TNIC	Sum of the similarity scores in the TNIC network	Hoberg and Phillips (2016)
Sales	Sales of the firm	Compustat
TA	Total asset of the firm	Compustat
AssetTangibility	property, plant and equipment over total assets	Compustat
CNInternet_Macro	The variable is constructed similarly to CNInternet. Instead of using the weights from public firms, we use the industry weights from the total assets information from China Data Online. We hand-matched each industry to 2-digit SIC industries.	CNNIC Reports; China Data Online
CNInternet_Top1	The variable is constructed similarly to CNInternet. Instead of using the value-weighted measure using all the provinces whose weights are above 10%, we put 100% weight on the province with the highest total assets of the industry	CNNIC Reports; Capital IQ; China Data Online

Appendix B. Robustness Tests

Table 14: Robustness - Weights from Macro Data

The table shows that our results are robust to the construction of the internet penetration ratio. Instead of using the public firms' data, we instead use the province-industry-level aggregate output to calculate the weights. The data is from ChinaDataOnline. The dependent variables in Columns (1)-(3) are the same as in Table 4; the dependent variables in Columns (4) and (5) are the same as in Table 6; the dependent variables in Columns (6) and (7) are the same as in Table 9. All dependent variables are measured in year $t+1$, and the independent variables are measured in year t. All variables are standardized to have unit variance for ease of interpretation. The sample includes all Compustat firms from 2001 to 2015 with available 10K filings on the EDGAR system. We exclude all observations where the total assets or sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp	CNCompHi	CNIntComp	$\frac{XRD}{Sales}$	$\frac{NPatent}{Sales}$	$\frac{PatCiteUS_{CN}}{Sales}$	$\frac{PatCiteCN}{Sales}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CNInternet_Macro	0.196***	0.157***	0.166***	−0.085***	−0.092***	0.345***	0.350***
	(0.044)	(0.044)	(0.044)	(0.021)	(0.031)	(0.048)	(0.042)
CNSalesGR	0.0004	−0.002	−0.002	0.005**	−0.0002	−0.002	0.00001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.106***	−0.109***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.039*	−0.046**	−0.014	−0.118***	−0.097***	0.075***	0.021
	(0.022)	(0.023)	(0.025)	(0.017)	(0.018)	(0.021)	(0.018)
log(TA)	0.047*	0.060**	0.034	0.033	−0.067**	−0.274***	−0.321***
	(0.028)	(0.027)	(0.031)	(0.028)	(0.029)	(0.033)	(0.033)
Industry Q	−0.017***	−0.015***	−0.020***	0.040***	0.028**	−0.049***	−0.022*
	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.011)	(0.012)
TNIC	−0.002	−0.002	−0.011*	0.037***	0.019**	−0.023**	0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,800	62,800	62,832	62,832

Table 15: Robustness - Top 1 provinces

The table shows that our results are robust to the construction of the internet penetration ratio. Instead of using a weighted-average measure, we use the internet penetration ratio from the province-year where the province has the most output for that industry. The dependent variables in Columns (1)-(3) are the same as in Table 4; the dependent variables in Columns (4) and (5) are the same as in Table 6; the dependent variables in Columns (6) and (7) are the same as in Table 9. All dependent variables are measured in year $t+1$, and the independent variables are measured in year t. All variables are standardized to have unit variance for ease of interpretation. The sample includes all Compustat firms from 2001 to 2015 with available 10K filings on the EDGAR system. We exclude all observations where the total assets or sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp	CNCompHi	CNIntComp	$\frac{XRD}{Sales}$	$\frac{NPatent}{Sales}$	$\frac{PatCiteUS_{CN}}{Sales}$	$\frac{PatCiteCN}{Sales}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CNInternet_Top1	0.114***	0.102***	0.112***	−0.111***	−0.109***	0.259***	0.243***
	(0.033)	(0.033)	(0.032)	(0.027)	(0.029)	(0.039)	(0.035)
CNSalesGR	0.0003	−0.002	−0.002	0.005***	0.0002	−0.002	−0.0004
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.106***	−0.110***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.055**	−0.058**	−0.027	−0.111***	−0.090***	0.048**	−0.006
	(0.022)	(0.023)	(0.025)	(0.016)	(0.018)	(0.020)	(0.018)
log(TA)	0.044	0.058**	0.032	0.034	−0.066**	−0.280***	−0.328***
	(0.028)	(0.027)	(0.031)	(0.028)	(0.029)	(0.034)	(0.033)
Industry Q	−0.017***	−0.015***	−0.020***	0.040***	0.028**	−0.049***	−0.022*
	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.011)	(0.012)
TNIC	−0.002	−0.002	−0.011*	0.038***	0.019**	−0.023***	0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,800	62,800	62,832	62,832

Table 16: Robustness of Table 6 Excluding Zero R&D Firms

This table tests the robustness of Table 6 by using subsample excluding observations where XRD/Sales equals 0. The dependent variable in Columns (1) - (3) is the R&D expenses over sales. For missing R&D, we follow the Koh and Reeb (2015) and replace the missing with industry average if the firm files for any patent patents applications in the past three years (including the current year), and 0 otherwise. The dependent variables are measures from 1, 2, or 3 years in the future. Note all the variables are normalized by the sales from year t. The dependent variable in Columns (4) - (6) is the total number of patent applications each year (by filing date) divided by sales. The patent data comes from Google Patents, and we match the patents to Compustat firms using the links from Kogan, Papanikolaou, Seru, and Stoffman (2016). The dependent variables are measures from 1, 2, or 3 years in the future. The key independent variable CNInternet is the Chinese internet penetration ratio. All independent variables are one-year lagged relative to the dependent variables. All the variables are normalized by their standard deviations for easier interpretation. The sample covers all Compustat firms from 2001 to 2015. We exclude all observations where the total asset or the sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix.

	XRD/Sales			NPatent / Sales		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	−0.381***	−0.444***	−0.486***	−0.138*	−0.144*	−0.162**
	(0.081)	(0.086)	(0.091)	(0.083)	(0.078)	(0.076)
CNSalesGR	0.011*	0.009	0.010	−0.001	0.012*	0.001
	(0.006)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)
log(Age + 1)	−0.311***	−0.304***	−0.321***	−0.280***	−0.312***	−0.309***
	(0.044)	(0.048)	(0.055)	(0.050)	(0.050)	(0.051)
log(TA)	−0.005	−0.095	−0.280***	−0.172***	−0.218***	−0.286***
	(0.055)	(0.061)	(0.066)	(0.059)	(0.058)	(0.056)
Industry Q	0.038**	0.054***	0.050***	0.024	−0.003	−0.014
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
TNIC	0.267**	0.340***	0.288*	0.074	0.185*	0.198*
	(0.110)	(0.132)	(0.150)	(0.094)	(0.104)	(0.107)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	28,185	24,603	21,389	28,185	24,603	21,389

Table 17: Robustness - Excluding joint ventures

The table shows that our results are robust to the possible biases from joint ventures. We exclude firms that have ever reported joint ventures with China in their 10-K filings. The dependent variables in Columns (1)-(3) are the same as in Table 4; the dependent variables in Columns (4) and (5) are the same as in Table 6; the dependent variables in Columns (6) and (7) are the same as in Table 9. All dependent variables are measured in year $t+1$, and the independent variables are measured in year t. All variables are standardized to have unit variance for ease of interpretation. The sample includes all Compustat firms from 2001 to 2015 with available 10K filings on the EDGAR system. We exclude all observations where the total assets or sales are smaller than one million dollars. Robust standard errors clustered by firms are reported in the parentheses. Detailed definitions of the variables can be found in Table 13 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	CNComp	CNCompHi	CNIntComp	$\frac{XRD}{Sales}$	$\frac{NPatent}{Sales}$	$\frac{PatCiteUS_{CN}}{Sales}$	$\frac{PatCiteCN}{Sales}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CNInternet	0.114***	0.102***	0.112***	−0.111***	−0.109***	0.259***	0.243***
	(0.033)	(0.033)	(0.032)	(0.027)	(0.029)	(0.039)	(0.035)
CNSalesGR	0.0003	−0.002	−0.002	0.005***	0.0002	−0.002	−0.0004
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.106***	−0.110***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.055**	−0.058**	−0.027	−0.111***	−0.090***	0.048**	−0.006
	(0.022)	(0.023)	(0.025)	(0.016)	(0.018)	(0.020)	(0.018)
log(TA)	0.044	0.058**	0.032	0.034	−0.066**	−0.280***	−0.328***
	(0.028)	(0.027)	(0.031)	(0.028)	(0.029)	(0.034)	(0.033)
Industry Q	−0.017***	−0.015***	−0.020***	0.040***	0.028**	−0.049***	−0.022*
	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.011)	(0.012)
TNIC	−0.002	−0.002	−0.011*	0.038***	0.019**	−0.023***	0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,899	62,899	62,899	62,800	62,800	62,832	62,832

Appendix C. China import penetration

In this section, we explain how we construct the import penetration variable from China. The variable is constructed by combining several databases. We obtain gross output by industry from the BEA's website. We also obtain import and export data from [Peter Schott's website][peter]. Formally, the import penetration variable is defined as

$$\text{Import Penetration}_{CN} = \frac{\text{Import}_{CN}}{\text{Gross Output + Total Import - Total Export}}$$

One particular challenge in merging these datasets is that BEA does not strictly follow a standard industry classification. According to BEA's website, "BEA's industry groupings generally follow the North American Industry Classification System"[14]. However, there are two types of exceptions. First, one BEA industry is often matched to several NAICS industries. Second, the links are not of the same granularity across BEA industries. For example, in the detailed industry gross output file from BEA, while most industries are matched to six-digit NAICS industries, some are matched to three-digit or even two-digit NAICS industries.

We construct the China import penetration variable with the following steps. First, we define industries using the four-digit NAICS codes, which are similar to the three-digit SIC industry classifications. Then we aggregate the import/export data, which uses a six-digit NAICS code, into four-digit NAICS code groups. Note several industries in the import/export data also only have two-digit or three-digit industry information. For these industries, we thus calculate the import penetration for the broader industries only.

Next, we merge the industry gross output data to the import/export data. Note for industries that have zero China import, the import penetration ratio is just zero. Therefore, the merge is essentially a "left join" with the import/export data as the master dataset.

In the merging process, there are 19 four-digit SIC industries in the import/export data that are not matched. We list the non-matched industries in the table below. Furthermore, we also provide the reasons for non-matching and our solutions to address the issue.

NAICS industry	Problem	How we handle the issue
1124	Multiple industries	Using NAICS industry 112

[14] https://www.bea.gov/resources/learning-center/what-to-know-industries. The BEA industry-NAICS link file can be downloaded from https://apps.bea.gov/industry/xls/underlying-estimates/GDPbyInd_VA_Components_1998-2017.xlsx. In the excel file, the tab named "NAICS code" contains the link table. A more detailed discussion of the industry classification methods can be found in https://www.bea.gov/sites/default/files/2018-04/2017-industry-code-guide.pdf
[peter]: http://faculty.som.yale.edu/peterschott/sub_international.htm

NAICS industry	Problem	How we handle the issue
1125	Multiple industries	Using NAICS industry 112
1129	Multiple industries	Using NAICS industry 112
1132	Only three-digit NAICS in BEA	Using NAICS industry 113
1134	Only three-digit NAICS in BEA	Using NAICS industry 113
1141	Only three-digit NAICS in BEA	Using NAICS industry 114
2111	Only three-digit NAICS in BEA	Using NAICS industry 211
3122	Missing in BEA	Using NAICS industry 312
3151	Only three-digit NAICS in BEA	Using NAICS industry 315
3152	Only three-digit NAICS in BEA	Using NAICS industry 315
3159	Only three-digit NAICS in BEA	Using NAICS industry 315
3161	Only three-digit NAICS in BEA	Using NAICS industry 316
3162	Only three-digit NAICS in BEA	Using NAICS industry 316
3169	Only three-digit NAICS in BEA	Using NAICS industry 316
9100	Missing in BEA	Drop from sample
9200	Missing in BEA	Drop from sample
9300	Missing in BEA	Drop from sample
9800	Missing in BEA	Drop from sample
9900	Missing in BEA	Drop from sample

After merging the two datasets, we are able to calculate the import penetration ratio for each industry. In the final step, we merge the import penetration to Compustat sample using NAICS codes. Consistent with our previous steps, we use four-digit NAICS codes as our main industries classification. If an observation from Compustat only has two-digit or three-digit NAICS code, we then use the import penetration ratio for that two-digit or three digit NAICS-industry instead. We keep the import penetration variable as missing if the NAICS code is missing.