NBER WORKING PAPER SERIES

INTERNET ACCESS AND U.S. - CHINA INNOVATION COMPETITION

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Working Paper 28231
http://www.nber.org/papers/w28231

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2020

We thank Adrien Matray and seminar participants at American University, Cornell, Florida State University, University of Florida, University of Georgia, Pennsylvania State University, Queens University, Southern Methodist University, Syracuse, Tsinghua University and conference participants at the American Finance Association, European Finance Association, Finance Organization and Markets virtual seminar, and the Midwest Finance Association for helpful comments. All errors are the authors' alone. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 28231
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JEL No. D43,F13,L21,L26,O31,O34

ABSTRACT

Using new measures of expanded Internet access in China and internet-based search, we examine how competitive shocks from China impact U.S. innovation through the markets for innovation and existing products. We identify shocks to innovation competition using the geography of Chinese internet penetration and Chinese import data. Increases in the ability of Chinese industry peers to gather knowledge through the internet are followed by reductions in U.S. R&D investment and subsequent patents, and increased patenting by Chinese firms. The new Chinese patents also cite the U.S. firms patents at a high rate, consistent with increased intellectual property competition.

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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 the impact of this rise 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 (IP) protection. 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 existing 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 an empirical question whether increased competition leads to increases or decreases in innovation spending.

The existing empirical evidence examines import trade shocks and subsequent changes in R&D but has not examined the first stage of competition in R&D itself. Examining R&D

following import trade shocks from China, Autor, Dorn, Hanson, Pisano, and Shu (forthcoming) find a negative relation between imports from China and U.S. firm R&D spending.[1] However, even this evidence is mixed as Bloom, Draca, and Van Reenen (2016) find that import trade shocks lead to increased R&D spending in a sample of European firms. We consider a new approach to this question that examines competition in innovation itself. We introduce a novel shock to the ability of Chinese firms to compete in knowledge creation through changes in the cost and ability of Chinese firms to access information over the internet. We use the staggered internet rollout in China across provinces to identify changes in the cost of accessing information for Chinese firms located in these provinces. We map these information access changes to Chinese competing firms using differential industry agglomeration by province. We also examine the extent to which U.S. firms complain more about Chinese competition and intellectual property theft after increases in internet penetration 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 and competition in 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 tariffs and imports relate to products that already exist, and thus their impact on intellectual property competition would be indirect and observed with delay.

We study the competitive impact of Chinese innovation on U.S. innovation using direct measures of Chinese firms' ability to access information about U.S. innovation over the internet. We propose that differential industry agglomeration and internet penetration at

[1] Hombert and Matray (2018) also examine U.S. firms following China imports, 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.

the province level in China can be used to generate variation in the capacity of Chinese firms to access information cheaply and challenge U.S. firm innovation. First and foremost, intellectual property is knowledge, and the internet has proven to be an efficient means for accumulating knowledge, especially when the knowledge resides overseas and is available online in electronic form. Indeed, a wealth of information on intellectual property, product market strategies, and the performance of U.S. firms is available from firm websites, patent filings, and required EDGAR filings. Thus, as regional Chinese firms gain greater access to the internet, they have access to information at a much lower cost that allows them to more effectively compete in innovation with rival U.S. firms.

Our main analysis examines how U.S. firms change their innovative investment in the face of changes in intellectual property 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 also realize fewer patents, and there is a material increase in Chinese patents in these same intellectual property markets. In particular, the new patents by Chinese inventors directly cite the existing technology of the U.S. firms treated by the shock. This crowding-out effect is linked to Chinese firms competing with U.S. firms as required under the exclusion requirement. Placebo tests indicate that firms from Europe, Japan and other major economies do not compete differently when Chinese internet penetration rises. These findings mitigate concerns that unobserved economic state variables might be driving our results.

Competition in the market for intellectual property has a strong industry-specific component. We thus use provincial industry 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 locations where each industry most agglomerates. Because internet penetration depends on the ability of unrelated utility companies (internet service providers) to provide digital infrastructure, its variation is plausibly exogenous (particularly when we additionally control for demand effects such as industry growth rates in China, and when we consider placebo tests). Intuitively, the provision of high quality internet depends on population distributions, geographic features, and the relative efficiency of local Internet Service Providers (ISPs). Province-level penetration thus varies substantially across provinces and over time.[2] This framework allows us to create an industry-year panel of instruments for Chinese innovation competition with adequate variation to test our key hypotheses even after including firm and year fixed effects.

We also assess the specific role of Chinese government support by considering Chinese government five-year plans, which list the industries that are strategically favored at any point in time. We find that U.S. firms reduce R&D and patents more aggressively when internet penetration is high and their focal industry is supported in the Chinese five-year-plan. However, our main innovation results remain significant even in the absence of Chinese government support, reinforcing the distinct importance of information access on innovation competition.

As we are careful to note limitations in our ability to establish causality, we conduct a number of tests that at least partially support the validity of our instrument. First, using textual analysis of U.S. firm 10-Ks, we find that U.S. firms complain more about competition specifically from China, especially in the context of intellectual property, when our industry-year measure of Chinese internet penetration is higher. Second, placebo tests indicate no evidence of similar complaints about competition from other regions of the world including Japan, Europe, Canada and Mexico. This placebo test has high power, as complaints about competition from these other regions are more common. It also mitigates concerns about unobserved industry state variables, as industry conditions typically have a global component that would trigger positive results in these placebo tests.

Going beyond competition complaints, we also predict and find analogous treatment effects using patent citations for Chinese citations and no placebo results for other countries

[2] Roberts and Whited (2013) suggest that variation along geographic dimensions has good properties for causal identification.

in other regions of the world. We find that our internet penetration measure significantly 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 - including Japan, European countries, as well as Canada. Finally, we also find higher rates of patents applied for by firms and inventors in China itself that cite these same treated 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.

We also examine the ex post performance and production strategies of treated U.S. firms. Our findings are consistent with U.S. firms re-optimizing their production and sourcing decisions after an increase in Chinese competition. In the face of increased Chinese innovation competition, sales growth of U.S. firms declines over the long run and U.S. firms also increase their sourcing of inputs from China. Thus, the increased competition from China also facilitates the ability of U.S. firms to purchase less expensive inputs from offshore sources.

Existing theory further predicts that our results regarding curtailed innovation investment might moderate for firms with existing physical assets as hypothesized by Bloom, Draca, and Van Reenen (2016). In particular, treated firms with more tangible and potentially "trapped" assets might have incentives to maintain high innovation levels to avoid high adjustment costs from downsizing. These firms should reduce innovation less following competitive shocks. We use the asset tangibility of U.S. firms as our measure of trapped assets and indeed find that firms with more tangible assets do maintain higher relative levels of R&D spending and patents in the face of increased competition.

Our findings regarding trapped assets provide new insights on the importance of an industry's initial conditions in shaping the ultimate impact of competition in innovation. Two competing forces - competition in IP and existing markets - can help to explain some of the disagreement in the empirical literature, which finds both positive and negative competitive effects on innovation. We conclude that at least two margins of competition need to be separately explored. Our main finding is that competition in the market for intellectual property itself has a sharp negative impact due to crowding-out effects. In contrast, increased innovation to escape competition is more likely when firms are competing in existing products with assets with high asset specificity (due to high cost of downsizing).

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 ex post Chinese firm patents we find suggests that IP theft can only be part of the story, as the foreign innovators are securing legal patent protection. However, this alone does not rule out IP theft as the ability to create the new patents may also be partially from stolen trade secrets or other IP 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 aims to understand the impact of foreign competition specifically on the domestic innovation production margin, and how it might differ from foreign competition on the existing products margin (the focus of most existing studies). We focus on U.S.-China competition due to its importance and the existence of relevant experiments. Our thesis is that foreign competition plays out on at least two competitive margins.

Competition in the U.S. domestic innovation market has been extensively studied.[3] 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 Chinese imports. However, no study to our knowledge has examined the impact of competition in knowledge production itself on U.S. patenting and 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 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 analogously cede a share of the future market.

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

[3] 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).

"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.

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: the market for existing products. We propose that the overall effect of Chinese competition on a domestic incumbent's innovation spending has two parts: that from (1) increased competition in the market for existing products and (2) increased competition in the market for innovation itself. Understanding both margins can help to reconcile the mixed evidence in the literature.

Our first hypothesis relates to the margin of competition for innovation.

Hypothesis H1: Increased foreign competition in innovation will reduce the value of the incumbent's growth options as the entrant will take a fraction of both current and future market share. This will reduce the incumbent domestic firm's innovation spending and patenting. In contrast, foreign entrants will increase patenting activity, especially in technologies related to those of the incumbent.

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 crowding out prediction should dominate. In contrast, because innovation can change the market structure of existing products (Sutton, 1991), the scenario can be more complex on the second margin: competition in the market for existing products.

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 increase product differentiation and escape competition.

Because predictions can be ambiguous, it is natural to ask if initial conditions moderate which outcome prevails: 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. If a firm has non-redeployable assets and adjustment costs are high, it has a strong incentive to maintain high production levels. By increasing innovation, such a firm can preserve pricing power while maintaining production.

Hypothesis H3: When domestic incumbents have non-redeployable assets, these firms will increase innovation spending, all else equal, to fully utilize 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 is from 2001 to 2016, with 62,899 firm-years from 8,584 unique firms.

We construct a set of country-specific competition complaint measures using text from 10-K filings. We use software from meta Heuristica LLC to process these 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 define CNcomp as the number of matching paragraphs normalized by the total number of paragraphs in the given 10-K document. We construct three more specific competition measures by additionally requiring matching paragraphs to contain a word from a third word list. First, we define CNCompHi (high competition), as additionally requiring one word from the following list: (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 define CNIntComp (competition in intellectual property) as additionally requiring both “intellectual” and “property” in matching paragraphs. Finally, we measure complaints about IP theft, CNIntTheft, by counting the number of paragraphs that contain the country name list (”China” or ”Chinese”), contain “intellectual property” or “trade secret”, and that also match one of the words in the following list: (infringe* OR theft* OR stolen* OR steal*). In addition to constructing the above ratio measures scaled by the total number of paragraphs, we also construct dummy variables equal to one if the given firm has at least one hit on a given query above. We also construct analogous measures for three other major economies in the world: Europe, North America (Canada and Mexico), and Japan. Table A1 provides additional detail.

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[4]. We winsorize all ratio variables at the 1% and the 99% level to control for outliers. Definitions for other control variables can be found in Table A1.

[4]Our results on R&D are robust if we do not fill missing R&D expenses following Koh and Reeb (2015), as shown in Table OA9 in the Online Appendix.

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[5]. The database contains over 90 million patent publications from the patent offices of 18 countries, including both the U.S. and China, among others. We also use patent data from Kogan, Papanikolaou, Seru, and Stoffman (2016) (KPSS hereafter), who kindly share this data on their website. A key advantage of KPSS data is the authors link patents to U.S. public firms. Google patent data also has the patents filed by foreign firms, which we use to assess Chinese patenting and to conduct our placebo tests based on firms from other countries filing in the U.S.

We first use patent applications to measure innovation activities and we extend the KPSS (which ends in 2010) using the Google data. To link the new Google patent data to public firms, we utilize links already developed by KPSS. First, we take the overlapping part of the Google data and the KPSS data[6] 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 also provides the country for each assignee[7], allowing us to identify U.S. patents assigned to foreign firms. We use this information to additionally measure the number of new Chinese patents that specifically cite the existing patents of U.S. firms, providing direct evidence on the intensity of learning by Chinese firms about specific (treated) U.S. firms. We also construct similar measures for the other major economies, which facilitate our key

[5] See https://cloud.google.com/blog/products/gcp/google-patents-public-datasets-connecting-public-paid-and-private-patent-data. The data is accessed through Google's BigQuery service

[6] 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 patent number and the grant date.

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

placebo tests.

Finally, Google also includes patents filed with China's Patent Office SIPO (State Intellectual Property Office of the People's Republic of China). This allows us to further check whether Chinese patents filed with SIPO also cite the patents of treated U.S. firms, allowing us to reinforce tests based on our previous measures that use only patents filed in the U.S.

3.3 Internet Penetration

Internet access in China has dramatically changed over the past two decades. In the early 2000s, fewer than 1% of the population in China had access to the internet, and by 2018, the number of internet users in China surpassed 800 million and internet penetration 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 more efficiently, and it is almost indispensible for 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 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. Importantly, these reports provide information separately for each Chinese province (excluding Hong Kong and Macau). We then collect population for each province using China Data Online and we then compute the internet penetration ratio for each province in each year.

Internet infrastructure has grown unevenly across provinces in each year. For example, Figure 2 plots the year in which each province experienced its largest increase in internet penetration, illustrating a highly scattered pattern. The telecommunication industry in China also has experienced drastic change. Prior to 1994, China had a single government unit that provided all phone and internet service: the Directorate General of Telecommunications, which was later registered as China Telecom. The monopoly structure changed in 1994 when

China introduced China Unicom to compete with China Telecom. Deregulation continued in the 1990s as China Telecom was broken into two companies, and other internet service providers such as China Net and China Railnet were established. By the end of 2001, China had seven telecommunications companies, each focused on different businesses and regions. For example, China Net, an internet service provider, mostly operated in 10 provinces in northern China. After the industry went through a round of consolidation by the end of 2008, only three companies remained, each covering all telecommunication services, namely China Telecom, China Mobile, and China Unicom. These industry changes directly impacted internet services. For example, Figure 2 shows that after China Net was acquired by China Unicom, three northern provinces—Liaoning, Shandong, and Jilin—experienced their largest increase in the internet penetration rate in 2009.

We compute a measure of internet penetration customized to each industry in each year. To do so, we compute the weighted-average level of internet penetration based on the provinces that are most important for the given industry. Supporting this approach, a large literature illustrates that industries cluster geographically[8]. Ideally, our weights would assess the total assets of all firms in each industry across provinces. However, detailed census data covering private firms is not publicly available, and thus we focus on Chinese public firms. To reduce the impact of endogeneity in the industry-province links, we derive geographic industry distributions using only data from the year 2000. We choose this year because the number of industries spanned by public firms reaches sufficient critical mass in this year, as shown in Figure 3. We consider all Chinese public firms with non-missing headquarter locations and assets in 2000. This includes 938 firms listed in mainland China (A-share) and Hong Kong[9]. For each 2-digit SIC industry, we compute province weights using the total assets of the given industry's public firms headquartered in the given province in 2000. We then set to zero any provinces whose weights are below 10%, and recalculate the

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

[9]We only consider the primary exchange for dual-listed companies. Our results are robust if we only use A-share public firms, as shown in Table OA1 of the Online Appendix.

weights using the remaining provinces. Figure 4 shows the industry weights and descriptions of each province. The color fill represents the sum of the weights of all the industries in each province, and darker color indicates higher weight loading. For each province, we also list the top six 2-digit SIC industries by total assets.[10]

An industry's internet penetration ratio in a given year is then computed as the weighted average yearly internet penetration ratios across the relevant provinces using the fixed year 2000 weights for each industry. As we discuss in the Online Appendix, our results are robust to three alternative constructions of industry-specific internet penetration. First, we use the internet penetration only from the top province with the largest assets in the industry (Online Appendix Table OA2). Second, we consider the opposite approach and exclude the top industry for each province, as the top industry might enjoy favorable policies (Online Appendix Table OA3). Third, we consider weights based on macro-level industry output for each province instead of public firm assets (Online Appendix Table OA4).[11]

4 Summary Statistics and Validation

4.1 Summary Statistics

Table 1 presents summary statistics for our 2001 to 2016 panel of 62,892 firm-year observations. The average industry internet penetration ratio is 36% for each firm-year. Roughly 5% of sample firms explicitly complain about competition from China, and 40% of these firms specifically mention intellectual property in their competition complaints. Figure 1 plots the incidence of U.S. firms complaining about both types of Chinese competition and illustrates that both rise dramatically during our sample.

Table 1 also shows that U.S. firms complain about European and North American

[10]Due to the 10% cutoff for industry weights, some provinces will show fewer than six industries.

[11]The macro-level data is based on aggregated Chinese census data acquired from China Data Online. One disadvantage of this data is that it only includes manufacturing industries. However, a benefit is that it includes both public and private firms.

(Canada and Mexico) competition at even higher unconditional rates than they complain Chinese competition. Chinese competition (scaled by document size and x 1000) 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 these 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 as placebos. However, this variable is just 0.04 for Japan, indicating its smaller relative economic size and distance from the U.S.

We find even larger contrasts for patent citation activity across these regions. The average intensity of Chinese firms citing U.S. patents is 2.36, while European, Japanese and North American citations of U.S. firm patents are 26.85, 23.88 and 5.06, respectively. Because the data is considerably richer for these regions than it is for China, it again follows that our placebo tests should be particularly strong. Despite this high power, we still find strong results for Chinese companies and no results for placebo tests using these other regions of the world.

Table 2 displays summary statistics at the firm level rather than at the firm-year panel level. In particular, we first calculate the mean value of each variable for each firm, and the table shows statistics for the resulting firm averages. The primary motive for reporting summary statistics both ways is to assess the distributions of our key variables for extreme values. As we will include firm and year fixed effects, such outliers could sway our findings.

As is well-known in the innovation literature, variables measuring R&D and patenting activity tend to be right-skewed. Consistent with the literature, we winsorize all variables at the 1%/99% level.[12] 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 results remain robust in key subsamples including the set of firms with positive R&D activity or in subsamples with above-median patenting activity. The results in the Appendix show that our findings are robust to the

[12]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.

excluding firms with no reported R&D, as well as in these subsamples.

4.2 Validation Test: EDGAR Downloads by Chinese Internet Users

In this section, we validate our measure of Chinese internet penetration by directly assessing the intensity of internet traffic from China targeting each U.S. firm in each year. 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 Chinese internet users specifically in this year. If additionally, the evolution of internet penetration in China is plausibly exogenous to broader industry conditions (a key threat to exclusion), we additionally predict no relationship for downloads by internet users in other (placebo) nations. Alternatively, if internet penetration was endogenously driven by unobserved industry state variables (violating exclusion), we instead would predict a strong link between Chinese internet penetration and observed downloads from other parts of the world (as industry conditions such as demand levels have a strong global component).

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 U.S. public firm in each year from 2004 to 2015. We exclude IP addresses that are likely web crawlers. 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[13]. As larger firms will have more visitors, we scale 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 and we estimate the following regression

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

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

where i represents firm, j represents industry, and t represents year.

The dependent variable is the EDGAR web visitor traffic described above and detailed variable descriptions are in Section 3.1 and in Table A1. CNInternet is our key internet penetration variable. $\boldsymbol{Z}$ 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 from Hoberg and Phillips (2006). 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 from Hoberg and Phillips (2006). Finally to control for the possibility that Chinese firms learn through joint ventures rather than the internet, we include the control variable JV, which measures the intensity of joint ventures with China for each 3-digit SIC industry-year[14]. 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 standard errors are clustered by firm. In Online Appendix Table OA8, we also show that our results are robust to clustering by Industry - Year.

Table 3 shows that Chinese internet penetration significantly predicts the intensity of EDGAR downloads of U.S. firm disclosures by Chinese internet users. The inclusion of firm fixed effects absorbs all firm-specific unobservable characteristics, and allows us to focus on rigorous within-firm effects. These results provide strong validation of our proposed mechanism: internet usage is a major tool for rapid information gathering of knowledge by overseas individuals. This, in turn, likely exposes treated U.S. 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.

[14] JV is calculated for each industry-year as JV = sum(Sales of firms that reported joint venture with China) / sum(Sales of all firms in the industry). Online Appendix Table OA6 further shows that our results are robust if we exclude U.S. firms that reported any joint ventures in China.

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 between our measure of Chinese internet penetration and observed internet traffic from 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 strong common global components, we would expect these placebo tests to fail and produce significant results. Our findings instead suggest that any link between internet penetration and industry conditions is likely small in magnitude.

4.3 Validation Test: Complaints about Chinese Competition

Our empirical strategy is based on the assumption that increased Chinese information gathering via the internet specifically shifts the innovation competition faced by treated U.S. firms (those facing higher Chinese internet penetration). We test this validating assumption directly using textual analysis of 10-Ks disclosed by U.S. firms during our sample period to determine if treated U.S. firms disclose more complaints specifically about Chinese competition, and specifically in the context of intellectual property. These tests aim to validate the power of our instrument regarding its predicted economic content for the U.S. firms.

Once again, our framework also allows for strong placebo tests based on the other major economies. If the exclusion requirement holds, Chinese internet penetration should not predict higher rates of complaints by U.S. firms about competition from Europe, North America (Canada and Mexico) and Japan. As noted earlier, these placebo tests have high power due to the fact that these other economic regions are large in scale and U.S. firms frequently summarize the intensity of competition from these regions. The key empirical question is if these complaints are 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 complain about competition specifically from Chinese firms. A one standard deviation increase of the internet penetration ratio leads to a 0.132 standard deviation increase, or a 68% 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 such complaint in its 10-K. Columns (3) and (4) of Table 4 show that internet penetration also significantly predicts complaints specifically noting that Chinese competition is high.

Our most direct tests are in the last four columns of Table 4. Internet penetration also significantly predicts U.S. firm complaints about competition that are specific to intellectual property (IP) discussions (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. We find that U.S. firms indeed complain more about IP theft when internet penetration rises.

The possibility of IP theft has been a centerpiece of recent public and political debates about trade conflicts between the U.S. and China. Although we do not draw strong conclusions with respect to IP theft, as complaints do not constitute proof that a crime has occurred, our finding that internet penetration significantly predicts IP theft complaints is suggestive of a potential link that can motivate future research. Also relevant, we later document increased patenting with USPTO by Chinese firms (discussed later), which suggests that a significant part of the Chinese competitive activity is transparent and legal given current USPTO rules. 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 then facilitates the subsequent seemingly-legal patents. Overall, our evidence of IP theft is thus far from decisive and we report this evidence mainly to motivate the importance of future research on IP theft.

Overall, Table 4 validates that internet penetration has strong links to the competitive pressures reported by U.S. firms, and especially regarding IP discussions.

4.4 Placebo Tests using Other Major Economies

Although the above validation tests produce positive results regarding the predicted economic content of Chinese internet penetration, other economic or industry factors might be correlated with this measure. To further examine the exclusion requirement, we construct analogous measures of competition complaints for other the major economies (Europe, Japan, and Canada and Mexico). Table 5 shows the results. For brevity we focus on complaints about competition and intellectual property theft. The table shows that Chinese internet penetration is not significantly related to complaints about competition from any of the placebo regions. This evidence further suggests that our internet penetration variable is not picking up content related to global industry conditions or competition, which would predict significant coefficients in these placebo tests.

We briefly note that we run an additional placebo tests later in the paper where we consider patenting activity by firms in these placebo nations. We again find positive results for Chinese firms and their link to Chinese internet penetration, but no significant results for firms in placebo nations despite the higher power available for the placebo tests. Collectively, these placebo tests suggest that it is unlikely that our internet penetration variable is significantly contaminated by an omitted industry state variable. These findings lend support to the interpretation that our results are consistent with Chinese access to information through internet penetration likely driving increases in competition on the innovation production margin.

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 and ex post patenting by treated U.S. firms. We do so by estimating the regression model specified in Equation 1 where the dependent variable is U.S. firms' R&D/sales or patents/sales.

Table 6 shows the results. Column (1), which uses R&D 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 -0.183 is significant at the 1% level, and indicates that R&D decreases by 0.183 standard deviations when Chinese internet penetration increases by one standard deviation. The coefficient remains significant when we examine two-year ahead R&D in Column (2) and three-year ahead R&D in Column (3). To ensure the results are not driven by changes in the denominator (the scaling factor), following convention, we scale both dependent variables by ex ante sales from year t.

We find similar results for the ex post patenting by 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 -0.074, indicating a decrease of 0.074 standard deviations 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 Online Appendix Table OA5, we also find consistent results when we only include observations with positive R&D. Collectively, it is unlikely that the skewed distribution of R&D, or reports of zero or missing R&D, can explain our results.

We 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 ex-post innovation rates for treated U.S. firms. This main result of our paper is new to the literature, which instead focuses on the margin of import competition through existing products.

5.2 Impact on Chinese Firms

Unlike broad industry conditions such as demand shocks, which predict same-sign results for U.S. firms, Chinese firms, and placebo nation firms, our competition hypothesis rather uniquely predicts opposite-sign results for U.S. and Chinese firms, and no results for placebo nation firms.

We now examine the relationship between ex ante internet penetration and the ex post number of new Chinese patents that directly cite the existing patents of treated U.S. firms. We use the country information of the first assignee for each patent to identify patents 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 Chinese patents (that cite each focal U.S. firm) as the dependent variable in Table 9. Columns (1) - (3) 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 economically large as a one standard deviation increase in internet penetration is followed by a 0.224 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 patent citations 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 that this variable is bounded in [0,1] and thus avoids outliers. We find that the results in Columns (4) to (6) are similar to our baseline results in Columns (1) to (3). Our results are thus not driven by broad increases in patent citations, but 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 0.098 to 0.194 standard deviations of these SIPO patents over the three ex post years. Columns (10) - (12) of Table 9 show that these results are robust using the alternative scaling used in Columns (4) to (6).

We also examine whether the firms subject to Chinese increased competition increased their mergers and acquisitions to buy innovation as a substitute for the decreased internal R&D spending that we find. We measure M&A activity using data from the Securities Data Corporation (SDC). We do not find any significant changes in ex post M&A activity.

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 spanned 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. Taken together with our finding that U.S. firms decrease patenting in these same technological markets, our results suggest that high Chinese 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 opportunities, and thus crowd-out the treated U.S. firms.

5.3 Impact on Firms in Placebo Tests

Analogous to our earlier placebo tests in Table 5 regarding competition complaints, we perform similar placebo tests for the ex post patenting results in the previous section. If the exclusion requirement is violated, we would expect to see significant increases in patents from placebo nations that cite these same U.S. firms when Chinese internet penetration increases.

Table 10 displays regressions similar to those in Table 9, except we replace the dependent variable with patenting activity by firms in each of the alternative placebo economies (Europe, Japan, and Canada and Mexico). Table 9 shows that, across all columns, we find no evidence that Chinese internet penetration predicts ex post patenting activity by firms in any of the placebo economies. 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 above. In fact, six of the nine regression coefficients have 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 Chinese internet penetration rather uniquely measures the ability of Chinese firms (and not placebo nation firms) to compete in the market for innovation on the global stage. These results are consistent with the validity of the exclusion requirement.

5.4 Competition in Innovation vs. Product Market Competition

To compare the two margins of competition - competition in innovation and competition from existing products - we follow the literature and use import penetration from China to measure China's competition in existing products. Appendix 6 provides the detailed steps regarding how we construct the import penetration variable. We then consider regressions that include both competition in existing products and competition in innovation (based on our internet penetration variable). Panel A of Table 7 displays the results for our R&D and patenting dependent variables. Columns (1)-(4) display results for R&D, and Columns (1)-(3) focus on 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 internet penetration or import penetration in Columns (1) and (2), and include both in Column (3). As the coefficients change little when included together, the impact of each competition margin is likely unique and not particularly correlated. Although both competition variables have negative coefficients, 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) analogously examine patenting activity. We find that import penetration (CNImport) significantly and negatively impacts U.S. firms' patenting activity, especially in the years after China's admission into the WTO in 2001. In contrast, CNInternet has a negative but insignificant coefficient estimate in Column (5) of Panel A. The results are similar when we include both competition variables in Column (7). This result illustrates the existing literature's finding of a large impact of imports after China's inclusion in the WTO. Interestingly, however, when we extend the sample to 2016 in Column (8), we find that the CNInternet becomes significant, while the coefficient for CNImport loses its significance. This suggests that internet penetration and competition in the market for IP production became the dominant margin for competition in more recent years, whereas competition in existing products (import penetration) was the dominant margin in earlier years.[15] These results also illustrate that the two competition margins have distinct effects and at different times, illustrating the importance of modeling both in related settings.

We further examine specifications that include CNImport alone in different sample peri-

[15]Column (4) in Panel B shows that CNImport is negative and weakly significant if we exclude the CNInternet variable.

ods in Panel B of Table 7. Consistent with ADHPS, Columns (1) and (3) show significant and consistent negative effects for CNImport in their sample, which begins in 1997.[16] Columns (2) and (4) of Panel B show that CNImport is negative and significant in our full sample when included in the regression without CNInternet, although Panel A Rows (4) and (8) show that CNInternet subsumes this significance when both are included.

These subsample results, which include years beyond those in existing studies, show that competition relating to innovation is growing in importance relative to competition from existing products. Competition from existing products measured using import penetration is mainly significant in earlier samples. This shift in later years is also consistent with Chinese import penetration reaching more stable levels in the later years, and thus our fixed effects absorb more of its variation. Our results thus 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 explore import penetration and competition in existing products.

5.5 Competition and Central Government Support

The Chinese government provides additional support for innovation in selected industries as part of its five-year-plans, which are published by the Chinese government and renewed in five year cycles. From a theoretical perspective, subsidies increase the incentives to innovate by lowering costs. Because subsidies can accelerate innovation when adequate knowledge is available, we predict that the impact of Chinese competition on U.S. firms will be particularly large in magnitude when both (A) government subsidies target the focal industry and (B) internet penetration and knowledge-availability is high.[17]

To implement this test, we extract lists of strategically favored industries from each five-

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

[17] We also examine if our results are driven by local provinces lobbying to gain internet access to help their largest industry. We thus examine if our results are robust to excluding the largest province for each industry when computing internet penetration. We present the results in Online Appendix Table OA3, which shows that our results are robust.

year-plan,[18] and define a dummy variable FYP that is one if a given industry is favored in the five-year-plan prevailing at the time. Our primary focus is on the interaction with internet penetration (CNInternet x FYP).

Table 13 reruns our main tests with both FYP and its key interaction with CNInternet included. The interaction term in Columns (4) to (7) show that US firms indeed reduce R&D more aggressively and patent less when Chinese internet penetration is high and the focal industry is supported under the prevailing five-year-plan. Moreover, we also find that the CNInternet levels term remains negative and significant especially for R&D, indicating that access to quality information remains important even in the absence of government subsidies. Additionally, rows (1) to (3) show that complaints about Chinese competition by U.S. firms remain significantly related to internet penetration (CNInternet) but the cross term with FYP is not significant. We conclude that our main result is robust and generally strongest in industries that receive support. Yet our results remain robust even in non-subsidized industries.

In a final test, we examine whether government support alone (without considering internet penetration) can also generate our results. We thus drop all terms relating to internet penetration in Online Appendix Table OA7, but we keep the FYP dummy. We find that FYP is not significant in any of our main tests with one exception: column (4) shows that FYP predicts lower U.S. firm R&D. We conclude that although government support matters, access to high quality information about U.S. firms is crucial to generating our main results.

5.6 Subsequent Firm Performance

In this section we examine the long-run firm performance of treated U.S. firms subsequent to the increases in Chinese internet penetration. Hombert and Matray (2018) 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 - however both sets of firms have negative long-run

[18] These data were gathered by Hong, Li, and Phillips (2020). We thank them for sharing the data.

performance. We examine both the long-run change in sales growth and we alsohow U.S. firms change their offshoring decisions following episodes of high Chinese internet penetration.

Table 11 examines ex post sales growth over 5 years and shows that sales growth declines over longer-term horizons when CNInternet is high. In particular, sales growth is significantly negative three to five years after Chinese internet penetration increases. The 3 year lag is consistent with the fact that shocks to R&D take time before they are commercialized. The decline in year three is 7% and this further declines to 10.8% by year five. Overall, these results are consistent with U.S. firms growing less in the face of Chinese competition. We also examine subsequent firm profits and find, in unreported results, that there are no significant changes. Given that profits do not decline, we investigate whether treated U.S. firms make offsetting changes in their offshoring decisions in response to increased Chinese competition.

5.7 Subsequent Firm Sourcing Decisions

Table 12 examines ex post offshoring decisions following increases in Chinese competition. We focus specifically on offshore operations in China and we examine both input sourcing from China and output exporting to China. We thus use the text-based offshore network data from Hoberg and Moon (2017) and Hoberg and Moon (2019). These measures are based on 10-K filings and use proximity searches to examine the content of text appearing within a 15 word window around each mention of the word China. This proximity search identifies words associated with purchasing input or with selling output, allowing us to identify which U.S. public firms are engaged in each activity. The offshore input dummy is one if the firm mentions purchasing inputs from China in the given year. The offshore output dummy is analogously based on mentions of selling output to China in the given year.

Table 12 shows that U.S. firms facing higher Chinese internet penetration respond by purchasing more inputs from China. However, they do not increase their offshore sales to China. Columns 1 - 3 show that the increased purchase of Chinese inputs is significant for all windows examined. The propensity to conduct offshore purchasing of inputs increases 5% in one year and 3.8% in year three. These results are consistent with U.S.firms re-optimizing their sourcing and production decisions when Chinese competition increases. Given that the sales decline but operating profits do not, this is consistent with firms sourcing less expensive inputs - a potential benefit for the U.S. firms. The ability to source more inputs from China in this scenario indicates that firms adjust on multiple margins when foreign innovation competition increases.

5.8 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 the asset composition of the affected U.S. firms. For example, competition in the market for existing products can either increase or decrease innovation for the affected U.S. firms. Moreover, U.S. firms having non-redeployable assets might have strong incentives to increase innovation spending on the margin. Such innovation can help firms to "escape competition".

The theory of Bloom, Draca, and Van Reenen (2016) suggests that firms with more trapped (non-redeployable) assets will have stronger incentives to preserve market share by increasing innovation following shocks to competition. When competition increases, treated firms will become more innovative after the shock's arrival. The prediction is that U.S. firms will increase innovation following such competitive shocks. We take this prediction to the data and measure the likely existence of trapped assets using the asset tangibility of the U.S. firms. We then rerun our main regressions after adding a dummy indicating above-median ex ante asset tangibility and also its interaction with CNInternet.

Table 14, 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. These results are consistent with trapped asset predictions. Moreover, high asset tangibility firms increase innovation relative to firms with less asset tangibility as the cross terms in Columns (4) to (7) are positive and significant at the 1% or 5% level.

Although these results support the theories of Bloom, Draca, and Van Reenen (2016) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) for these firms with existing assets with high asset tangibility, our broader results show that this outcome is not observed in all situations. In particular, the sample-wide results strongly support that innovative activities are decreased when competitive shocks arrive. These different results in subsamples of firms with existing assets with high asset tangibility helps to resolve disagreement in the literature regarding the impact of foreign competition on domestic innovative activities. These results also reinforce the importance of initial conditions such as asset composition in moderating the incentives to increase or decrease innovation.

6 Conclusions

We examine the impact of Chinese innovation competition on U.S. firm R&D and patenting activity. We use Chinese province-level data on internet penetration and geographic industry agglomeration data to identify variation in the capacity of Chinese firms to challenge U.S. firms on the knowledge-centric margin of innovation production. Validation tests support for this interpretation of internet penetration. Higher internet penetration predicts higher web traffic from China specifically accessing information about the impacted U.S. firms, and textual analysis of SEC filings indicates that impacted U.S. firms complain more about Chinese competition, especially regarding intellectual property. Placebo tests help mitigate concerns that Chinese internet penetration is influenced by unobserved industry conditions.

Our main conclusion is that increased intellectual property competition has a strong and robust negative impact on U.S. firm R&D spending, realized patents, and subsequent long-run sales growth. At the same time, Chinese firms increase their patenting activity specifically in the area of the afflicted U.S. firms. These results indicate a crowding-out effect as the foreign rivals capture a fraction of the rents of innovation. The results are consistent with higher internet penetration decreasing the cost of obtaining information for competing firms. The magnitude of these results increases for industries that are strategically favored by the Chinese government, but remain significant even for non-favored industries.

Our results regarding competition in innovation are distinct from earlier findings relating to competition from existing products. Both competitive margins are independently significant and is important at different points in time. Competition in existing products is most important following China's 2001 entry into the WTO, and competition in innovation production is most important later following increased internet penetration in China.

Overall, our results help to reconcile disagreement in the literature regarding whether foreign 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.

References

Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005, Competition and innovation: an inverted u relationship, *Quarterly Journal of Economics* 120, 701–28.

Autor, David, David Dorn, Gordon H Hanson, Gary Pisano, and Pian Shu, forthcoming, Foreign competition and domestic innovation: Evidence from us patents.", *American Economic Review: Insights.*

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923–1960.

Bloom, Nicholas, Mirko Draca, and John Van Reenen, 2016, Trade induced technical change? the impact of chinese imports on innovation, IT and productivity, *Review of Economics Studies* 83, 87–117.

Duranton, Gilles, and Henry G Overman, 2005, Testing for localization using micro-geographic data, *The Review of Economic Studies* 72, 1077–1106.

——— , 2008, Exploring the detailed location patterns of uk manufacturing industries using microgeographic data, *Journal of Regional Science* 48, 213–243.

Ellison, Glenn, and Edward L Glaeser, 1997, Geographic concentration in us manufacturing industries: a dartboard approach, *Journal of political economy* 105, 889–927.

Florence, Philip Sargant, 1948, *Investment, location, and size of plant* . vol. 7 (CUP Archive).

Fuchs, Victor R, 1962, The determinants of the redistribution of manufacturing in the united states since 1929, *Review of Economics and Statistics* 44, 167–177.

Hoberg, Gerard, and S Katie Moon, 2017, Offshore activities and financial vs operational hedging, *Journal of Financial Economics* 125, 217–244.

——— , 2019, The offshoring return premium, *Management Science* 65, 2876–2899.

Hoberg, Gerard, and Gordon Phillips, 2006, Real and financial industry booms and busts, Working Paper, University of Maryland.

Hombert, Johan, and Adrien Matray, 2018, Can innovation help us manufacturing firms escape import competition from china?, *The Journal of Finance* 80, 2003–2039.

Hong, Xiangjun, Minwen Li, and Gordon Phillips, 2020, Influence activities and regulating chinese acquisitions, *Working paper.*

Hoover, Edgar M, 1948, *Location of economic activity* (McGraw-Hill Book Company, Inc., New York).

Kogan, Leonid, Dimtris Papanikolaou, Amit Seru, and Noah Stoffman, 2016, Technological innovation, resource allocation and growth, *Quarterly Journal of Economics* forthcoming.

Koh, Ping-Sheng, and David Reeb, 2015, Missing r&d, *Journal of Accounting and Economics* pp. 73–94.

Krugman, Paul R, 1993, *Geography and trade* (MIT press).

Lee, Charles M C, Paul Ma, and Charles C Y Wang, 2015, Search-based peer firms: Aggregating investor perceptions through internet co-searches, *Journal of Financial Economics* 116, 410–431.

Phillips, Gordon M., and Alexei Zhdanov, 2013, R&d and the incentives from merger and acquisition activity, *Review of Financial Studies* 34-78, 189–238.

Reinganum, Jennifer F, 1989, The timing of innovation: Research, development, and diffusion, *Handbook of industrial organization* 1, 849–908.

Roberts, Michael R, and Toni M Whited, 2013, Endogeneity in empirical corporate finance1, in *Handbook of the Economics of Finance*vol. 2 . pp. 493–572 (Elsevier).

Sutton, John, 1991, *Sunk Costs and Market Structure* (MIT Press: Cambridge, Mass).

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 A1

Variable	N	Mean	Std. Dev.	Median	75th	95th	99th
CNInternet	62892	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	62892	0.15	0.77	0.00	0.00	0.00	5.63
CNComp Dummy	62892	0.05	0.21	0.00	0.00	0.00	1.00
CNCompHi % x 1000	62892	0.09	0.51	0.00	0.00	0.00	3.85
CNCompHi Dummy	62892	0.03	0.18	0.00	0.00	0.00	1.00
CNIntComp % x 1000	62892	0.05	0.32	0.00	0.00	0.00	2.51
CNIntComp Dummy	62892	0.02	0.15	0.00	0.00	0.00	1.00
CNIntTheft % x 1000	62892	0.02	0.26	0.00	0.00	0.00	0.00
CNIntTheft Dummy	62892	0.01	0.10	0.00	0.00	0.00	0.00
EUComp % x 1000	62892	0.26	1.13	0.00	0.00	1.96	5.62
EUCompHi % x 1000	62892	0.14	0.78	0.00	0.00	0.00	3.83
EUIntComp % x 1000	62892	0.11	0.66	0.00	0.00	0.00	3.28
JPComp % x 1000	62892	0.04	0.26	0.00	0.00	0.00	2.18
JPCompHi % x 1000	62892	0.01	0.07	0.00	0.00	0.00	0.69
JPIntComp % x 1000	62892	0.02	0.31	0.00	0.00	0.00	0.00
NAComp % x 1000	62892	0.24	0.93	0.00	0.00	1.96	6.15
NACompHi % x 1000	62892	0.10	0.53	0.00	0.00	0.00	3.85
NAIntComp % x 1000	62892	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	62892	3.28	35.51	0.00	0.00	5.00	66.00
PatCiteUS$_{CN}$	62892	2.36	31.85	0.00	0.00	3.00	40.00
PatCiteUS$_{EU}$	62892	26.85	237.32	0.00	1.00	57.00	549.00
PatCiteUS$_{JP}$	62892	23.88	286.82	0.00	0.00	34.00	357.71
PatCiteUS$_{NA}$	62892	5.06	53.76	0.00	0.00	11.00	93.00
PatCiteUS$_{US}$	62892	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	62892	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	62892	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 A1

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. 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 A1 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	# of EDGAR searches / Sales			
	CN	EU	JP	NA
	(1)	(2)	(3)	(4)
CNInternet	0.105**	−0.012	0.042	0.019
	(0.045)	(0.041)	(0.043)	(0.038)
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)	−0.227***	−0.431***	−0.203***	−0.418***
	(0.041)	(0.044)	(0.041)	(0.044)
Industry Q	0.006	0.014	−0.016	0.025
	(0.013)	(0.016)	(0.018)	(0.017)
TNIC	0.013	0.011	0.014	0.018*
	(0.012)	(0.011)	(0.012)	(0.009)
JV	0.017	−0.001	0.038	0.003
	(0.050)	(0.036)	(0.035)	(0.042)
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 competition discussion is truly about China. More detailed variable construction procedures can be found in Table A1 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 A1 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***	0.153***	0.122***	0.141***	0.114***	0.132***	0.080**	0.096***
	(0.038)	(0.040)	(0.036)	(0.039)	(0.038)	(0.039)	(0.038)	(0.036)
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)	−0.107***	−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**	−0.050**	−0.057**	−0.053**	−0.026	−0.022	−0.020	−0.018
	(0.022)	(0.022)	(0.023)	(0.023)	(0.025)	(0.025)	(0.026)	(0.023)
log(TA)	0.043	0.026	0.056**	0.038	0.031	0.025	0.074***	0.068***
	(0.028)	(0.027)	(0.027)	(0.026)	(0.031)	(0.030)	(0.028)	(0.025)
Industry Q	−0.018***	−0.017***	−0.016***	−0.014**	−0.021***	−0.020***	−0.020***	−0.010
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)
TNIC	−0.004	−0.005	−0.005	−0.008	−0.013**	−0.013**	−0.006	−0.010**
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)
JV	0.020***	0.020***	0.027***	0.026***	0.011	0.011	0.005	0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,892	62,892	62,892	62,892	62,892

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 A1 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	JP		NA		EU	
	IntComp	IntTheft	IntComp	IntTheft	IntComp	IntTheft
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	0.010	−0.011	0.044	0.000	0.040	0.009
	(0.033)	(0.011)	(0.040)	(0.000)	(0.047)	(0.024)
CNSalesGR	−0.001	−0.001	0.0001	0.000	−0.0004	−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)	0.036**	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	0.131***	0.000	0.202***	0.087***
	(0.034)	(0.008)	(0.031)	(0.000)	(0.039)	(0.021)
Industry Q	0.007	0.003	0.010	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)
JV	−0.003	−0.0003	0.003	0.000	−0.007	0.001
	(0.007)	(0.001)	(0.008)	(0.000)	(0.007)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,892	62,892	62,892

Table 6: U.S. Firm Innovation activities and Chinese internet penetration

The table displays OLS regressions in which the dependent variables are U.S. 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 A1 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	−0.172***	−0.194***	−0.203***	−0.090**	−0.083**	−0.082**
	(0.036)	(0.039)	(0.040)	(0.037)	(0.034)	(0.033)
CNSalesGR	0.005**	0.003*	0.003	−0.0004	0.006***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Age + 1)	−0.114***	−0.109***	−0.100***	−0.091***	−0.102***	−0.094***
	(0.016)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
log(TA)	0.036	−0.004	−0.103***	−0.067**	−0.087***	−0.115***
	(0.027)	(0.030)	(0.032)	(0.029)	(0.028)	(0.027)
Industry Q	0.037***	0.049***	0.044***	0.026**	0.007	0.001
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
TNIC	0.039***	0.041***	0.035***	0.020**	0.031***	0.029***
	(0.010)	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)
JV	0.003	0.006*	0.005	−0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	62,738	54,626	47,413	62,738	54,626	47,413

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 U.S. firm R&D expenses divided by the sales in the previous year, and the dependent variables in Columns (5)-(8) are the number of U.S. firm 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 A1 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	−0.176**		−0.176**	−0.182***	−0.098		−0.077	−0.088**
	(0.081)		(0.088)	(0.039)	(0.086)		(0.093)	(0.038)
CNImport		−0.015	−0.006	0.011		−0.035**	−0.032*	−0.005
		(0.011)	(0.013)	(0.007)		(0.017)	(0.018)	(0.014)
CNSalesGR	0.005	0.004	0.004	0.005**	0.001	0.00001	0.0004	−0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
log(Age + 1)	−0.155***	−0.155***	−0.157***	−0.115***	−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)	0.114***	0.113***	0.112***	0.037	−0.014	−0.020	−0.020	−0.068**
	(0.037)	(0.038)	(0.037)	(0.028)	(0.042)	(0.043)	(0.043)	(0.029)
Industry Q	0.038***	0.038***	0.038***	0.037***	0.033**	0.032**	0.032**	0.026**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)
TNIC	0.054***	0.052***	0.054***	0.039***	0.035***	0.034**	0.035***	0.020**
	(0.014)	(0.014)	(0.014)	(0.010)	(0.013)	(0.013)	(0.013)	(0.008)
JV	0.008	0.008	0.008	0.004	0.003	0.003	0.003	−0.003
	(0.006)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	32,766	32,539	32,539	62,248	32,766	32,539	32,539	62,248

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: U.S. Innovation activities and Chinese internet penetration - Poisson Regression

The table displays poisson regressions in which the dependent variables are U.S. 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 A1 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	-0.544***	-0.568***	-0.605***	-0.276***	-0.330***	-0.397***
	(0.059)	(0.061)	(0.066)	(0.098)	(0.100)	(0.105)
CNSalesGR	-0.037*	-0.063***	-0.054**	-0.040**	-0.011	-0.045**
	(0.019)	(0.022)	(0.024)	(0.020)	(0.020)	(0.019)
log(Age + 1)	-0.190***	-0.167***	-0.128***	0.010	-0.033	0.008
	(0.021)	(0.023)	(0.024)	(0.033)	(0.037)	(0.033)
log(AT)	-0.598***	-0.658***	-0.693***	-0.430***	-0.435***	-0.475***
	(0.028)	(0.027)	(0.030)	(0.036)	(0.037)	(0.039)
Industry Q	0.091***	0.096***	0.074***	0.049**	0.056**	0.031
	(0.019)	(0.020)	(0.021)	(0.021)	(0.023)	(0.023)
TNIC	0.218***	0.210***	0.195***	0.108***	0.081*	0.083*
	(0.029)	(0.031)	(0.032)	(0.040)	(0.045)	(0.046)
Lagged XRD/Sales	0.243***	0.238***	0.236***			
	(0.025)	(0.026)	(0.027)			
Lagged NPatent/Sales				0.214***	0.205***	0.215***
				(0.022)	(0.023)	(0.027)
Year FE	Y	Y	Y	Y	Y	Y
N	60,689	52,790	45,834	60,689	52,790	45,834

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 U.S. firm's existing patents. In Columns (1) - (3), for each firm we count the number of new patents that have cited the U.S. 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 new 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 A1 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	0.228***	0.175***	0.155***	0.213***	0.223***	0.196***	0.218***	0.139***	0.107***	0.297***	0.271***	0.271***
	(0.049)	(0.046)	(0.047)	(0.041)	(0.042)	(0.044)	(0.040)	(0.037)	(0.040)	(0.043)	(0.046)	(0.050)
CNSalesGR	−0.0004	0.003	0.007*	0.001	0.006	0.015***	0.001	0.007**	0.012***	−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)	0.053***	0.062***	0.029	−0.062***	−0.047**	−0.030	−0.002	0.004	0.003	−0.424***	−0.403***	−0.384***
	(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***	−0.266***	−0.213***	−0.107***	−0.092***	−0.081***	−0.328***	−0.322***	−0.286***	−0.025	−0.045	−0.049
	(0.033)	(0.035)	(0.035)	(0.026)	(0.028)	(0.030)	(0.033)	(0.034)	(0.037)	(0.028)	(0.029)	(0.031)
Industry Q	−0.051***	−0.042***	−0.052***	−0.044***	−0.042***	−0.037***	−0.025**	−0.030***	−0.023*	−0.002	−0.005	−0.004
	(0.011)	(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***	−0.014	−0.004	−0.012	−0.004	−0.007	−0.0003	−0.003	−0.007	0.015**	0.015**	0.018**
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
JV	−0.012***	−0.003	0.004	−0.002	−0.002	−0.002	−0.008*	−0.005	−0.008	0.006	0.001	−0.009
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)
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	62,831	54,626	47,413	62,831	54,761	47,581	62,831	54,626	47,413	62,831	54,761	47,581

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 firm's existing patents. We define the dependent variables as in the Columns (1)-(3) of Table 9. $\text{PatCiteUS}_{it}^{JP}$ are the number of patents, which are filed by Japanese firms with USPTO in year t, that cite firm i's existing patents. Similarly, $\text{PatCiteUS}_{it}^{NA}$ are the patent counts filed by firms from Canada or Mexica, and $\text{PatCiteUS}_{it}^{EU}$, 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 A1 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	−0.017	−0.048	−0.066	0.026	0.053	0.025	−0.006	−0.039	−0.038
	(0.040)	(0.042)	(0.046)	(0.040)	(0.039)	(0.044)	(0.040)	(0.040)	(0.045)
CNSalesGR	−0.001	0.005**	−0.003	−0.004*	0.002	−0.002	−0.0003	0.002	0.00004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
log(Age + 1)	0.071***	0.034*	0.027	0.077***	0.066***	0.057***	0.067***	0.011	0.027
	(0.016)	(0.017)	(0.019)	(0.017)	(0.018)	(0.019)	(0.015)	(0.017)	(0.017)
log(TA)	−0.187***	−0.190***	−0.030	−0.207***	−0.217***	−0.101***	−0.193***	−0.171***	−0.056*
	(0.029)	(0.034)	(0.035)	(0.029)	(0.032)	(0.030)	(0.030)	(0.031)	(0.032)
Industry Q	−0.029***	0.004	−0.005	−0.022	0.001	−0.003	−0.025**	0.008	−0.003
	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)	(0.014)	(0.012)	(0.013)	(0.013)
TNIC	0.016**	0.026***	0.002	−0.015*	−0.009	−0.013	0.001	0.025***	−0.0001
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
JV	−0.005	0.002	0.001	−0.002	−0.001	−0.001	−0.005	−0.001	−0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	62,831	54,626	47,581	62,831	54,626	47,581	62,831	54,626	47,581

Table 11: U.S. Firm Long-term Performance

The table displays OLS regressions in which the dependent variables are the sales growth of U.S. firms. The dependent variable is the change of log(Sales) from the previous year. 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 A1 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Δlog(Sales)				
	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
CNInternet	0.030	0.008	−0.070*	−0.098**	−0.108***
	(0.034)	(0.036)	(0.037)	(0.038)	(0.041)
CNSalesGR	0.012***	0.004	0.004	0.015***	0.010
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
log(Age + 1)	−0.340***	−0.158***	−0.072***	−0.035	−0.051*
	(0.022)	(0.022)	(0.023)	(0.026)	(0.030)
log(TA)	−0.443***	−1.004***	−0.857***	−0.703***	−0.495***
	(0.029)	(0.030)	(0.034)	(0.038)	(0.040)
Industry Q	0.155***	−0.030***	−0.029**	−0.052***	−0.049***
	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
TNIC	0.005	−0.028**	−0.010	0.012	0.017
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)
JV	0.004	−0.004	−0.007	−0.0005	0.002
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	62,251	54,344	47,250	40,908	35,188

Table 12: U.S. Firm Off-Shoring Acitivities

The table displays OLS regressions in which the dependent variable is a dummy variable indicating whether U.S. firms purchase inputs from China (Columns 1 - 3) or sell outputs to China (Columns 4 - 6). To measure offshore purchases from China or the sale of output to China, we use the text-based offshore network data from Hoberg and Moon (2017) and Hoberg and Moon (2019). These measures are based on 10-K filings and use proximity searches to examine the vocabulary within a 15 word window surrounding each mention of the word China. The proximity search identifies words associated with purchasing input or with selling output, allowing us to identify which U.S. public firms are engaged in each activity. The offshore input dummy is one if the firm mentions an instance of purchasing inputs from China at least once. The offshore output variable is analogously based on whether the firm mentions an instance of selling output to China at least once. 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 A1 in the Appendix. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Offshore_Input			Offshore_Output		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
CNInternet	0.050***	0.043***	0.038***	0.009	0.003	−0.003
	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)
CNSalesGR	0.0001	−0.0003	−0.0004	0.001	−0.0004	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Age + 1)	−0.011	−0.010	−0.005	−0.029***	−0.030***	−0.033***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
log(TA)	0.019**	0.013	0.008	0.034***	0.029***	0.026**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)
Industry Q	−0.006***	−0.004*	−0.003	−0.007**	−0.007**	−0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
TNIC	−0.007***	−0.005**	−0.004	−0.003	−0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
JV	0.011***	0.009***	0.009***	0.008***	0.006**	0.006**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	65,219	56,657	49,097	65,219	56,657	49,097

Table 13: Subsample analysis - by Five Year Plans

This table re-estimates regressions in Table 4 and 6 with an additional variable, FYP, which equals to 1 if the industry was of strategic focus for development in China's five year plans for the relevant five-year periods. We interact the FYP dummy with the Chinese internet penetration variable. 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 A1 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 FYP	−0.016	0.002	−0.034	−0.204***	−0.298***	−0.216***	−0.242***
	(0.028)	(0.031)	(0.035)	(0.060)	(0.081)	(0.059)	(0.067)
CNInternet	0.123***	0.119***	0.113***	−0.151***	−0.167***	−0.057*	−0.041
	(0.036)	(0.035)	(0.037)	(0.031)	(0.032)	(0.034)	(0.028)
CNSalesGR x FYP	−0.033**	−0.021	−0.021	0.043	0.004	0.019	0.028
	(0.017)	(0.021)	(0.022)	(0.028)	(0.034)	(0.034)	(0.026)
CNSalesGR	0.001	−0.001	−0.001	0.005**	0.003	0.0003	0.003*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
FYP	0.041	0.022	0.095	0.226*	0.369***	0.426***	0.414***
	(0.051)	(0.055)	(0.075)	(0.123)	(0.126)	(0.127)	(0.107)
log(10kSize)	−0.107***	−0.110***	−0.099***				
	(0.010)	(0.010)	(0.011)				
log(Age + 1)	−0.053***	−0.057***	−0.026	−0.114***	−0.096***	−0.087***	−0.091***
	(0.021)	(0.022)	(0.023)	(0.015)	(0.018)	(0.017)	(0.017)
log(TA)	0.043	0.057**	0.032	0.036	−0.077***	−0.072***	−0.113***
	(0.026)	(0.025)	(0.029)	(0.026)	(0.028)	(0.028)	(0.026)
Industry Q	−0.017***	−0.015***	−0.020***	0.036***	0.054***	0.025**	0.007
	(0.005)	(0.005)	(0.006)	(0.012)	(0.011)	(0.012)	(0.011)
TNIC	−0.004	−0.005	−0.012**	0.038***	0.043***	0.020**	0.033***
	(0.005)	(0.004)	(0.006)	(0.009)	(0.010)	(0.008)	(0.008)
JV	0.020***	0.027***	0.011	0.004	0.006*	−0.002	0.004
	(0.007)	(0.008)	(0.007)	(0.003)	(0.003)	(0.002)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	47,528	62,738	47,528

Table 14: 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 the U.S. 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 A1 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	0.033**	0.026*	0.040**	0.063***	0.055***	0.047***	0.053***
	(0.015)	(0.015)	(0.016)	(0.013)	(0.015)	(0.013)	(0.013)
CNInternet	0.097**	0.101**	0.082**	−0.215***	−0.240***	−0.122***	−0.112***
	(0.040)	(0.040)	(0.040)	(0.044)	(0.049)	(0.043)	(0.039)
CNSalesGR x HighT	0.006	0.005	0.006	−0.002	0.002	0.004	−0.0001
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
CNSalesGR	−0.002	−0.005	−0.004	0.007*	0.002	−0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
HighT	0.001	0.005	0.016	−0.098***	−0.106***	−0.043*	−0.069***
	(0.023)	(0.023)	(0.026)	(0.022)	(0.025)	(0.026)	(0.024)
log(10kSize)	−0.112***	−0.115***	−0.101***				
	(0.011)	(0.012)	(0.012)				
log(Age + 1)	−0.047*	−0.053**	−0.017	−0.117***	−0.103***	−0.105***	−0.099***
	(0.026)	(0.027)	(0.029)	(0.019)	(0.022)	(0.021)	(0.021)
log(TA)	0.047	0.064**	0.038	0.037	−0.108***	−0.072**	−0.123***
	(0.030)	(0.029)	(0.033)	(0.029)	(0.034)	(0.031)	(0.029)
Industry Q	−0.014**	−0.012**	−0.016**	0.033**	0.036**	0.026*	−0.003
	(0.006)	(0.006)	(0.007)	(0.013)	(0.014)	(0.014)	(0.014)
TNIC	−0.004	−0.005	−0.013**	0.044***	0.040***	0.023**	0.032***
	(0.006)	(0.005)	(0.006)	(0.011)	(0.012)	(0.009)	(0.009)
JV	0.020***	0.027***	0.010	0.002	0.004	−0.003	0.002
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	59,638	59,638	59,638	59,359	44,779	59,359	44,779

Figures

Figure 1: Complaints about Chinese competition

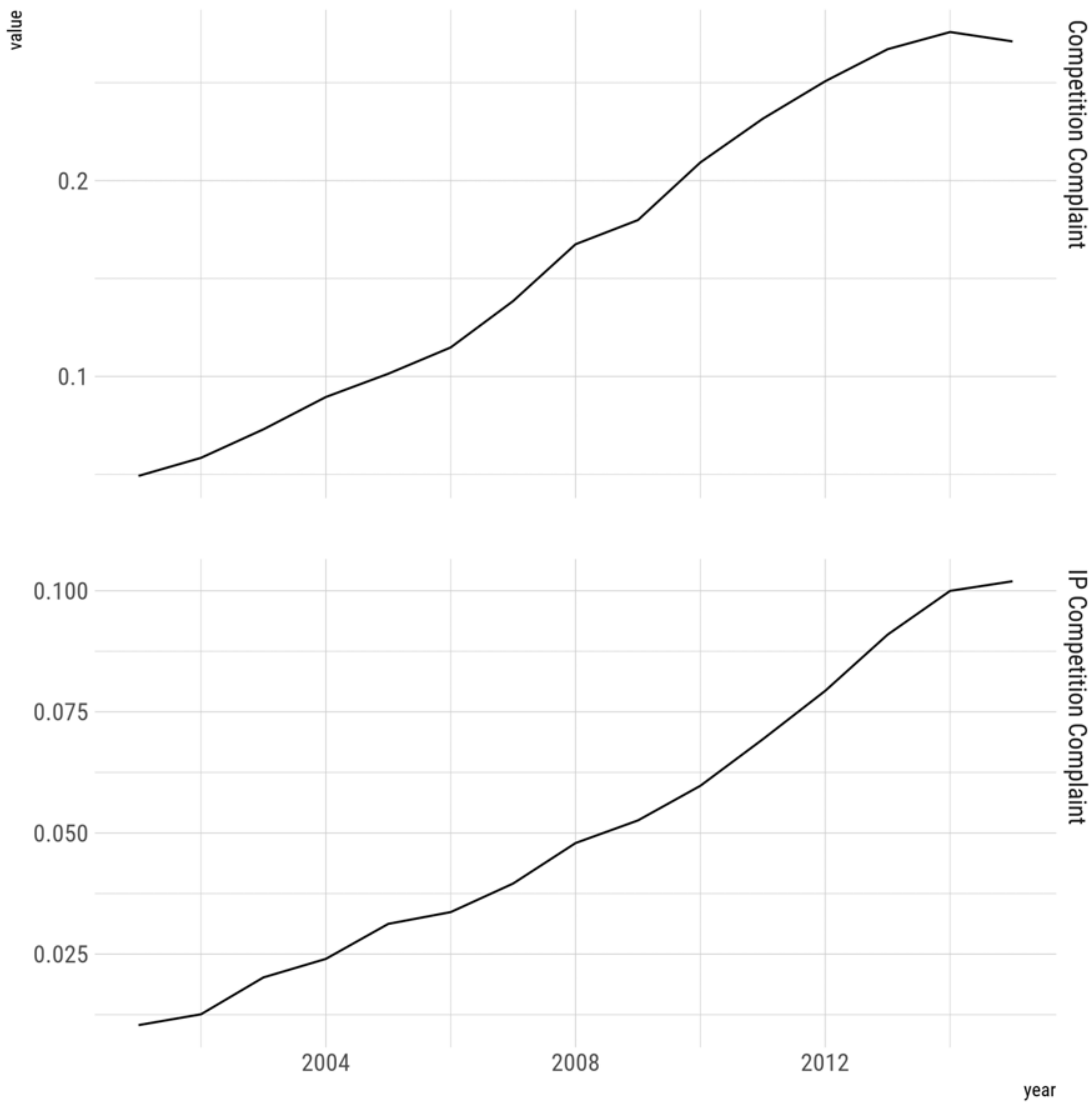


Figure 2: Internet penetration growth variation

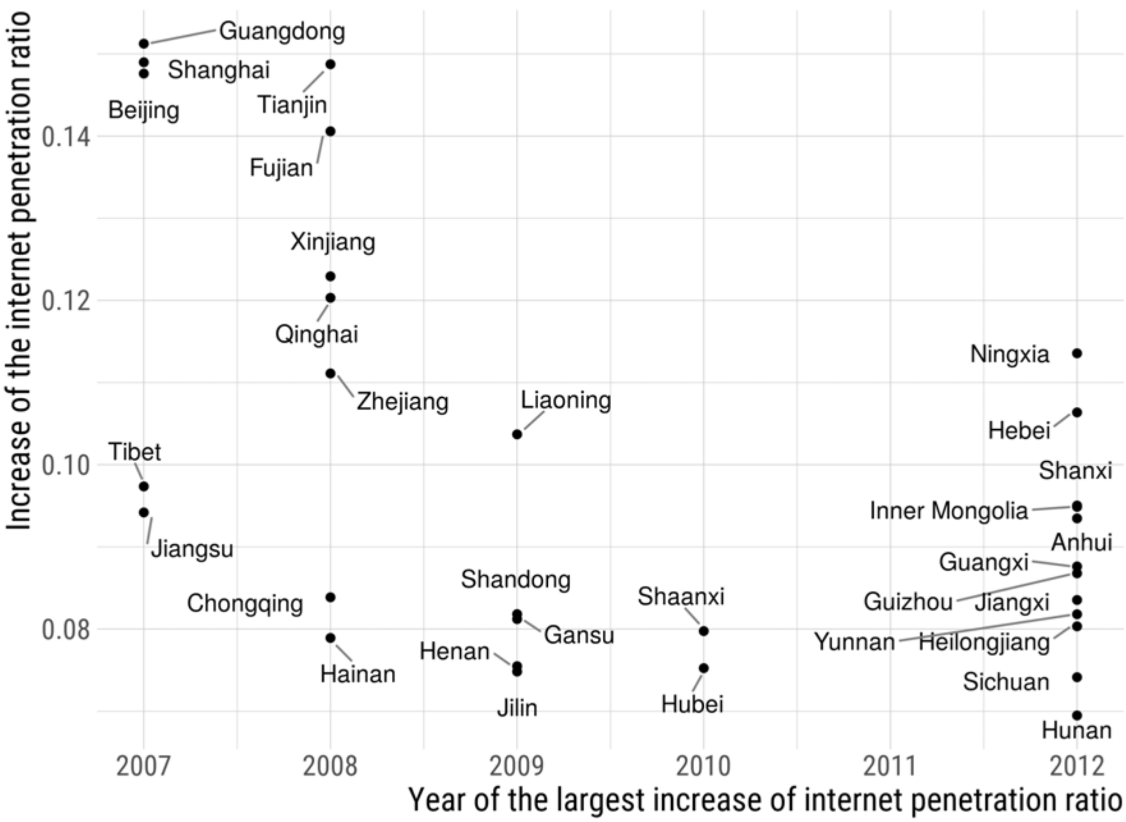


Figure 3: Number of industries (SIC2) covered by Chinese public firms

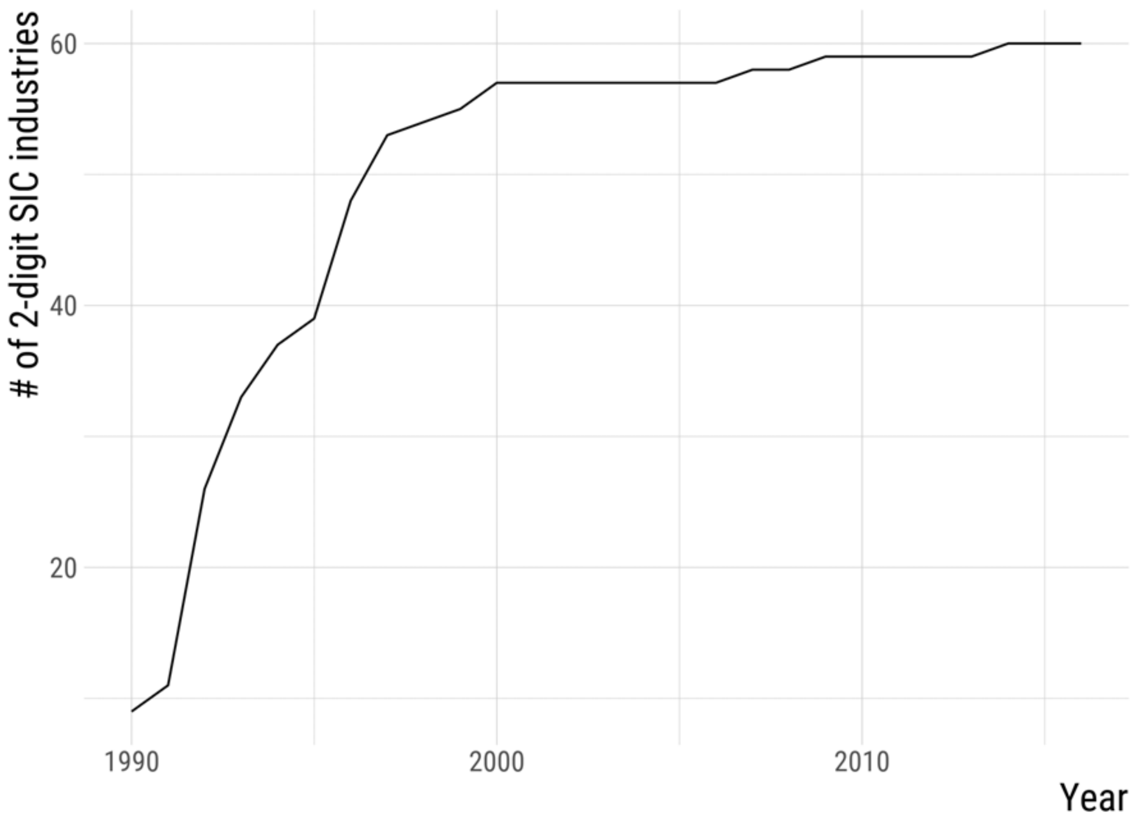
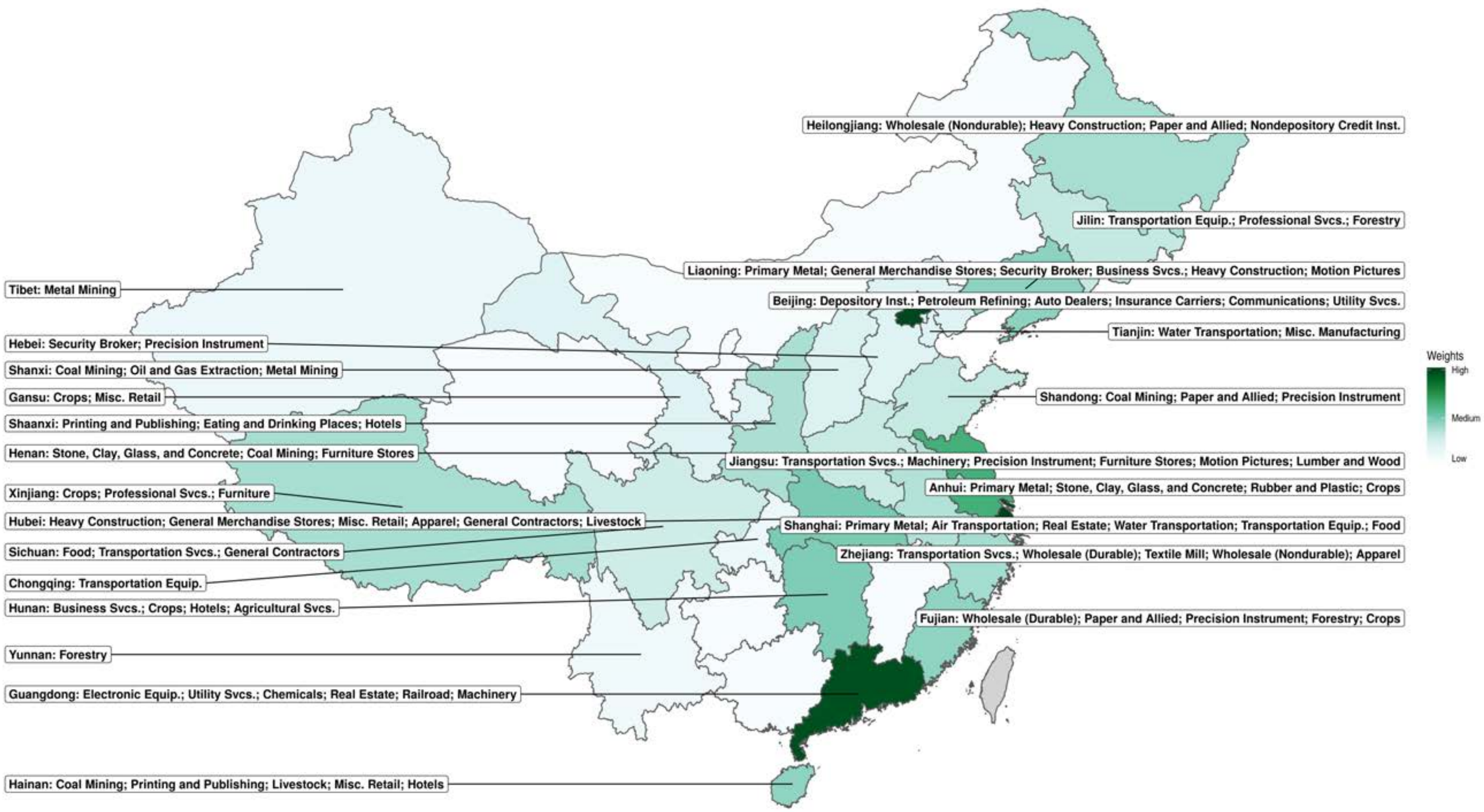


Figure 4: Industry-Province weight loading



Appendix A. Variable definitions

Table A1: Variable definitions

Table A1

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 only) 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

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Table A1 – *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)
JV	Joint venture intensity for each 3-digit SIC industry-year. It is calculated as: for each 3-digit SIC industry-year, JV = sum of the sales of all firms that have mentioned "joint venture" in their 10K filings / sum of sales of all firms	Hoberg and Phillips (2016); Compustat
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

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Table A1 – *Continued from previous page*

Variable	Definition	Source
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

Online Appendix: Not for publication

A. Robustness Checks

Table OA1: Robustness - Weights using China-A-share firms

The table shows that our results are robust to the construction of the internet penetration ratio. In particular, we restrict the universe of public firms to only A-share firms, or firms that are listed on the Shanghai or Shenzhen Stock Exchanges. 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 A1 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_Ashare	0.132***	0.109***	0.115***	−0.181***	−0.072*	0.224***	0.194***
	(0.036)	(0.036)	(0.038)	(0.037)	(0.037)	(0.049)	(0.041)
CNSalesGR	0.0005	−0.002	−0.002	0.005***	−0.0003	−0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.107***	−0.110***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.053**	−0.057**	−0.025	−0.114***	−0.091***	0.053***	−0.002
	(0.022)	(0.023)	(0.025)	(0.016)	(0.018)	(0.020)	(0.018)
log(TA)	0.045	0.058**	0.033	0.033	−0.068**	−0.277***	−0.326***
	(0.028)	(0.027)	(0.031)	(0.027)	(0.029)	(0.033)	(0.033)
Industry Q	−0.018***	−0.016***	−0.021***	0.037***	0.026**	−0.051***	−0.025**
	(0.005)	(0.006)	(0.006)	(0.012)	(0.013)	(0.011)	(0.012)
TNIC	−0.004	−0.004	−0.012**	0.038***	0.020**	−0.024***	0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
JV	0.021***	0.027***	0.011	0.003	−0.003	−0.012***	−0.008*
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.004)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA2: Robustness - Top Internet Penetration Year

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 A1 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	0.127***	0.123***	0.099***	−0.115***	−0.091***	0.167***	0.202***
	(0.031)	(0.031)	(0.032)	(0.024)	(0.027)	(0.037)	(0.031)
CNSalesGR	−0.0002	−0.002	−0.002	0.006***	0.0003	−0.002	−0.0002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.107***	−0.110***	−0.098***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.052**	−0.056**	−0.025	−0.114***	−0.092***	0.054***	−0.00004
	(0.022)	(0.023)	(0.025)	(0.016)	(0.018)	(0.020)	(0.018)
log(TA)	0.042	0.055**	0.030	0.037	−0.067**	−0.282***	−0.329***
	(0.028)	(0.027)	(0.031)	(0.027)	(0.029)	(0.034)	(0.033)
Industry Q	−0.018***	−0.016***	−0.021***	0.037***	0.026**	−0.051***	−0.025**
	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.011)	(0.012)
TNIC	−0.004	−0.005	−0.012**	0.038***	0.020**	−0.025***	−0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
JV	0.020***	0.027***	0.011	0.004	−0.002	−0.013***	−0.009*
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.004)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA3: Robustness - Excluding the Largest Industry in Each Province

The table excludes the largest industry in each province to examine if local government pressure or lobbying for this industry impacts our results. 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 A1 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	0.100***	0.095***	0.063**	−0.190***	−0.088***	0.103***	0.158***
	(0.032)	(0.031)	(0.031)	(0.036)	(0.033)	(0.038)	(0.034)
CNSalesGR	0.001	−0.001	−0.001	0.005***	−0.0003	−0.0005	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.106***	−0.110***	−0.097***				
	(0.010)	(0.010)	(0.011)				
log(Age + 1)	−0.050**	−0.054**	−0.024	−0.120***	−0.094***	0.055***	0.003
	(0.021)	(0.022)	(0.023)	(0.015)	(0.017)	(0.019)	(0.017)
log(TA)	0.041	0.054**	0.029	0.039	−0.065**	−0.284***	−0.332***
	(0.026)	(0.025)	(0.029)	(0.025)	(0.027)	(0.031)	(0.031)
Industry Q	−0.018***	−0.016***	−0.021***	0.037***	0.026**	−0.051***	−0.025**
	(0.005)	(0.005)	(0.006)	(0.012)	(0.012)	(0.011)	(0.011)
TNIC	−0.003	−0.004	−0.011*	0.037***	0.019**	−0.022***	0.002
	(0.005)	(0.004)	(0.006)	(0.009)	(0.008)	(0.008)	(0.008)
JV	0.019***	0.026***	0.010	0.005*	−0.002	−0.014***	−0.010**
	(0.007)	(0.008)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA4: 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 A1 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	0.194***	0.155***	0.165***	−0.083***	−0.090***	0.345***	0.350***
	(0.044)	(0.044)	(0.043)	(0.021)	(0.031)	(0.048)	(0.042)
CNSalesGR	0.0001	−0.002	−0.002	0.005***	−0.0001	−0.002	0.0002
	(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)	−0.040*	−0.047**	−0.015	−0.118***	−0.097***	0.076***	0.021
	(0.022)	(0.023)	(0.025)	(0.017)	(0.018)	(0.021)	(0.018)
log(TA)	0.046	0.058**	0.034	0.036	−0.068**	−0.274***	−0.321***
	(0.028)	(0.027)	(0.031)	(0.027)	(0.029)	(0.033)	(0.033)
Industry Q	−0.017***	−0.015***	−0.020***	0.036***	0.026**	−0.049***	−0.022*
	(0.005)	(0.006)	(0.006)	(0.013)	(0.013)	(0.011)	(0.012)
TNIC	−0.003	−0.003	−0.011*	0.036***	0.019**	−0.023**	0.001
	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)
JV	0.019***	0.026***	0.010	0.004	−0.002	−0.014***	−0.010**
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.004)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA5: 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 A1 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	−0.343***	−0.385***	−0.399***	−0.124*	−0.133**	−0.139**
	(0.069)	(0.073)	(0.077)	(0.070)	(0.066)	(0.066)
CNSalesGR	0.012*	0.009	0.009	−0.0005	0.013*	0.003
	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
log(Age + 1)	−0.314***	−0.299***	−0.314***	−0.281***	−0.311***	−0.305***
	(0.044)	(0.049)	(0.056)	(0.051)	(0.050)	(0.052)
log(TA)	0.004	−0.075	−0.257***	−0.175***	−0.222***	−0.288***
	(0.054)	(0.061)	(0.065)	(0.060)	(0.059)	(0.057)
Industry Q	0.035**	0.051***	0.042**	0.022	−0.006	−0.017
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
TNIC	0.270**	0.347***	0.259*	0.078	0.196*	0.207*
	(0.110)	(0.132)	(0.148)	(0.094)	(0.105)	(0.108)
JV	0.0003	0.004	0.005	−0.006	−0.00004	0.002
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	28,177	24,574	21,360	28,177	24,574	21,360

Table OA6: 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 A1 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	0.079**	0.092***	0.077**	−0.209***	−0.106***	0.263***	0.223***
	(0.035)	(0.034)	(0.035)	(0.042)	(0.041)	(0.051)	(0.044)
CNSalesGR	−0.001	−0.001	−0.001	0.004**	0.0002	0.00003	0.002
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.076***	−0.077***	−0.066***				
	(0.009)	(0.010)	(0.010)				
log(Age + 1)	−0.025	−0.026	−0.005	−0.115***	−0.093***	0.051**	0.00002
	(0.019)	(0.021)	(0.021)	(0.017)	(0.019)	(0.021)	(0.019)
log(TA)	0.040	0.039	0.030	0.034	−0.064**	−0.258***	−0.310***
	(0.024)	(0.024)	(0.027)	(0.029)	(0.031)	(0.034)	(0.034)
Industry Q	−0.015***	−0.011**	−0.021***	0.033**	0.025*	−0.049***	−0.027**
	(0.005)	(0.005)	(0.006)	(0.013)	(0.013)	(0.012)	(0.012)
TNIC	−0.005	−0.006	−0.014***	0.036***	0.022***	−0.021**	0.0004
	(0.004)	(0.004)	(0.005)	(0.010)	(0.008)	(0.009)	(0.009)
JV	0.009	0.013*	0.0002	0.005	−0.002	−0.014***	−0.006
	(0.006)	(0.007)	(0.007)	(0.004)	(0.003)	(0.005)	(0.006)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	56,198	56,198	56,198	55,900	55,900	55,993	55,993

Table OA7: Innovation Activities of Firms in Targeted Industries in Five Year Plans

The table shows how our variables of interests differ for five-year plans-targeted versus non-targeted industries. The key independent variable is FYP, which equals to 1 if the industry was of strategic focus for development in China's five year plans for the relevant five-year periods. 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 A1 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)
FYP	0.016	0.036	0.038	−0.180**	−0.003	0.086	−0.055
	(0.037)	(0.041)	(0.047)	(0.086)	(0.072)	(0.069)	(0.055)
CNSalesGR	0.001	−0.001	−0.002	0.005***	0.001	−0.0004	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log(10kSize)	−0.107***	−0.110***	−0.099***				
	(0.010)	(0.010)	(0.011)				
log(Age + 1)	−0.054***	−0.058***	−0.027	−0.111***	−0.084***	0.051***	−0.004
	(0.021)	(0.022)	(0.023)	(0.015)	(0.017)	(0.019)	(0.017)
log(TA)	0.041	0.055**	0.031	0.038	−0.070**	−0.282***	−0.332***
	(0.026)	(0.025)	(0.029)	(0.026)	(0.028)	(0.032)	(0.031)
Industry Q	−0.017***	−0.015***	−0.020***	0.034***	0.023*	−0.051***	−0.025**
	(0.005)	(0.005)	(0.006)	(0.012)	(0.012)	(0.011)	(0.011)
TNIC	−0.002	−0.003	−0.010*	0.035***	0.019**	−0.021**	0.003
	(0.005)	(0.004)	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
JV	0.020***	0.026***	0.010	0.004	−0.002	−0.014***	−0.010**
	(0.007)	(0.008)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA8: Robustness - Clustering Standard Errors by Industry x Year

The table shows the regression results with standard errors clustered by 3-digit SICxYear. 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 3-digit SIC Industry x Year are reported in the parentheses. Detailed definitions of the variables can be found in Table A1 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	0.122***	0.122***	0.114***	−0.172***	−0.090***	0.228***	0.218***
	(0.026)	(0.025)	(0.029)	(0.046)	(0.031)	(0.054)	(0.049)
CNSalesGR	0.001	−0.001	−0.001	0.005*	−0.0004	−0.0004	0.001
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.005)
log(10kSize)	−0.107***	−0.110***	−0.097***				
	(0.008)	(0.009)	(0.009)				
log(Age + 1)	−0.053***	−0.057***	−0.026	−0.114***	−0.091***	0.053***	−0.002
	(0.014)	(0.015)	(0.016)	(0.020)	(0.017)	(0.015)	(0.014)
log(TA)	0.043***	0.056***	0.031*	0.036**	−0.067***	−0.280***	−0.328***
	(0.015)	(0.015)	(0.017)	(0.016)	(0.017)	(0.030)	(0.031)
Industry Q	−0.018***	−0.016***	−0.021***	0.037***	0.026***	−0.051***	−0.025**
	(0.004)	(0.004)	(0.005)	(0.010)	(0.010)	(0.010)	(0.012)
TNIC	−0.004	−0.005	−0.013**	0.039***	0.020**	−0.025***	−0.0003
	(0.005)	(0.005)	(0.006)	(0.012)	(0.009)	(0.009)	(0.007)
JV	0.020***	0.027***	0.011*	0.003	−0.003	−0.012***	−0.008
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	62,738	62,831	62,831

Table OA9: Robustness of Table 6 Not Filling Missing R&D

This table tests the robustness of Table 6 by not filling missing R&D as in Koh and Reeb (2015). The dependent variable in Columns (1) - (3) is the R&D expenses over sales. 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 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 A1 in the Appendix.

	XRD/Sales		
	t+1	t+2	t+3
	(1)	(2)	(3)
CNInternet	-0.171^{***}	-0.200^{***}	-0.215^{***}
	(0.034)	(0.036)	(0.038)
CNSalesGR	0.003^{***}	0.002	0.002
	(0.001)	(0.001)	(0.001)
log(Age + 1)	-0.120^{***}	-0.111^{***}	-0.104^{***}
	(0.015)	(0.016)	(0.018)
log(TA)	0.047^{*}	0.002	-0.095^{***}
	(0.025)	(0.028)	(0.031)
Industry Q	0.039^{***}	0.050^{***}	0.047^{***}
	(0.012)	(0.012)	(0.012)
TNIC	0.039^{***}	0.043^{***}	0.037^{***}
	(0.010)	(0.010)	(0.011)
JV	0.003	0.005^{**}	0.005^{*}
	(0.002)	(0.002)	(0.003)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N	62,738	54,626	47,413

B. Additional Tests

B.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 OA10 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 -0.061, almost half the size of the coefficient of the internet penetration variable itself, which is -0.150. 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.

Table OA10: Subsample analysis - by Q

This table re-estimates regressions in Table 4 and 6 with an additional variable, HighQ, which equals to 1 if the U.S. 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 responses 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 A1 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**	0.026**	0.021	−0.062***	−0.064***	−0.047***	−0.058***
	(0.012)	(0.012)	(0.014)	(0.010)	(0.014)	(0.011)	(0.012)
CNInternet	0.105***	0.107***	0.102***	−0.140***	−0.174***	−0.066*	−0.056*
	(0.039)	(0.037)	(0.038)	(0.033)	(0.036)	(0.034)	(0.030)
CNSalesGR x HighQ	0.0002	−0.001	0.003	0.006	−0.004	−0.001	0.006*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
CNSalesGR	0.001	−0.001	−0.003	0.002	0.006***	0.00004	−0.0001
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
HighQ	−0.029	−0.035*	−0.040**	0.078***	0.063***	0.021	0.055***
	(0.018)	(0.018)	(0.019)	(0.018)	(0.020)	(0.020)	(0.019)
log(10kSize)	−0.106***	−0.110***	−0.097***				
	(0.010)	(0.011)	(0.011)				
log(Age + 1)	−0.052**	−0.057**	−0.026	−0.116***	−0.102***	−0.095***	−0.096***
	(0.022)	(0.023)	(0.025)	(0.016)	(0.019)	(0.018)	(0.018)
log(TA)	0.040	0.054**	0.028	0.042	−0.097***	−0.065**	−0.110***
	(0.028)	(0.027)	(0.031)	(0.027)	(0.032)	(0.029)	(0.027)
Industry Q	−0.018***	−0.014***	−0.018***	0.033**	0.041***	0.032**	−0.001
	(0.006)	(0.005)	(0.006)	(0.014)	(0.015)	(0.014)	(0.014)
TNIC	−0.003	−0.004	−0.012**	0.036***	0.033***	0.018**	0.027***
	(0.005)	(0.005)	(0.006)	(0.010)	(0.011)	(0.008)	(0.008)
JV	0.021***	0.028***	0.011	0.003	0.004	−0.003	0.003
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N	62,892	62,892	62,892	62,738	47,413	62,738	47,413

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. 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"[19]. 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
1125	Multiple industries	Using NAICS industry 112

[19] `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
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.