Impact of Competition on Innovations of IT Industry: An Empirical Investigation

Tao Chen

Nanyang Business School, Nanyang Technological University

jtchen@ntu.edu.sg

Hsing Kenneth Cheng

Warrington College of Business, University of Florida

hkcheng@ufl.edu

Yong Jin

Faculty of Business, The Hong Kong Polytechnic University

jimmy.jin@polyu.edu.hk

Shengli Li

Department of Information Management, Peking University

lishengli@pku.edu.cn

Liangfei Qiu

Warrington College of Business, University of Florida

liangfei.qiu@warrington.ufl.edu

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Abstract

Innovation and competition are two major pillars in the IT industry. In this paper, we examine the causal relationship between product market competition and innovations in the IT industry. We measure the innovations from both the quantity (number of patents) and the quality (number of non-self citations) perspectives. Based on the Herfindahl-Hirschman Index and natural experiments, we find robust evidence that the competition has a positive effect on the innovations of the IT industry. Specifically, after the exogenous shock to the market (import tariff cuts and thus increased industry competition), the number of patents per IT firm increases by 27.3%, and the number of non-self citations per IT firm increases by 38.2% on average. The effects are more pronounced in the more competitive sectors. Our study highlights the importance of the competition in the IT industry and suggests that the positive effect of competition on innovation in the IT context is likely to be driven by the parallel search effect. Our findings contribute to the recent policy debate and suggest that reducing import barriers may bring important welfare gains through innovations in the IT industry.

Keywords: *Product Market Competition, Innovation, Information Technology, Patent, Import Tariff*

"The preinvention monopoly power acts as a strong disincentive to further innovation."

— Arrow (1962, page 620)

"As soon as we go into details and inquire into the individual items in which progress was most conspicuous, the trail leads not to the doors of those firms that work under conditions of comparatively free competition but precisely to the doors of the large concerns . . . and a shocking suspicion dawns upon us that big business may have had more to do with creating that standard of life than with keeping it down."

— Schumpeter (1942, page 82)

Introduction

Innovations establish the firms' competitive advantages and contribute to the firms' competitive success in the Information Technology (IT) industry (Porter, 1992; Kleis et al., 2012; Gomber et al., 2018; Gozman et al., 2018; Lehrer et al., 2018; Qiu et al., 2019; Rivera et al, 2021). The recent rapid development of the IT industry, which is widely regarded as an increasing "knowledge intensity" industry (El Sawy et al., 1999; Fichman and Melville, 2014) with the market competition as the systemic feature (McAfee and Brynjolfsson, 2008; Cheng et al. 2011; Ren and Dewan, 2015), requires high standards of the firm-level innovations to "manipulate the competitive forces in their industry in order to achieve comparative advantage over competitors" (Bakos and Treacy, 1986). Therefore, it is of interest to study the behaviors of the firm-level innovations under the competitive environment in the IT industry and identify the determinant of the innovations.

The effect of competition on innovation has been a controversial subject in both theory and empirical evidence. In particular, what market structure best promotes innovation? The theoretical debate is dominated by a negative "Schumpeter effect" versus a positive "Arrow effect" of competition on innovation. Schumpeter (1942) argues that innovation is attributable to large firms operating in oligopolistic markets, not to small firms operating in competitive markets. In other words, substantial market power and the prospect of earning monopoly profits provide incentives

and the ability for large firms to undertake risky, innovative activities. Aghion and Howitt (1992) formalize Schumpeter's idea in an analytical model and demonstrate a negative impact of competition on innovation. The underlying intuition is that if innovation is driven by the expectation of higher profits in the future, then an increase in competition will lower the benefit of innovation and reduce innovation. By contrast, Arrow (1962) points out that a monopolist has less incentive to innovate than a firm in a competitive industry does. The reason is that a firm earning substantial monopoly profits has an interest in protecting the status quo and is thus less likely to innovate.

Both directions are theoretically plausible, providing a viable opportunity for empirical testing. Aghion et al. (2005) reconcile these two views, finding an inverted-U relationship between competition and innovation in the manufacturing industry: If the initial degree of competition is low, there is a positive impact of competition on innovation; if the initial degree of competition is high, increasing competition reduces innovation. However, the empirical findings in Aghion et al. (2005) have been questioned by Correa (2012) and Hashmi (2013). Using the same dataset, Correa (2012) shows that taking a structural break into consideration, the inverted-U empirical relationship between innovation and competition found by Aghion et al. (2005) does not hold. Hashmi (2013) finds a mildly negative relationship between competition and innovation. Several other studies also suggest that there is no consensus about the effects of the competition on innovations based on empirical evidence (e.g., Blundell et al. 1999, Kim et al. 2016, Tang 2006). An interesting discussion has also been extended to the IT platforms and IT industry.

In particular, Khan (2017, 2018) argues that IT platforms, such as Amazon, experience flagging competition in corresponding industries or sectors – the enhanced market power can manifest as non-price harms such as diminished innovations. Therefore, the antitrust and Big

Tech's monopolistic practices become an unsolved but critical question – Investigation of Competition in the Digital Markets, for the House Judiciary Committee's Subcommittee on Antitrust, Commercial and Administrative Law, which raises the concerns about fewer innovations, fewer customers' choices, and weakened democracy in the presence of the relatively less competition in the digital markets and IT industry.

The key causal identification issue here is that competition (measured as market concentration or firms' profitability) is both a cause and an effect of innovation and technological change. Cornaggia et al. (2015) argue that innovations are "likely endogenous with company and market characteristics." As a result, the causal relationship between competition and innovation is not straightforward and can depend on other unobservable features, a view consistent with previous theoretical findings in the literature (e.g., Bonanno and Haworth, 1998, Nelson and Winter, 2009).

The major challenge to empirically discern the effect of competition on innovations is to cleanly identify the causal relationship between the market condition and firm-level innovations because innovations are endogenously determined with the firm and market characteristics. Aghion et al. (2018) design two laboratory experiments to analyze the causal effects of competition on innovation. However, laboratory settings may suffer a severe lack of external validity in our context. To address these challenges, we construct the tests based on not only the traditional economic measures of industry competitiveness (Hirschman, 1964), but also on the implementation of import tariff cuts as exogenous shocks in the market competition (Frésard, 2010; Valta, 2012) since the import tariff cuts lead to increased foreign competition and thus greater product market competition in the U.S. domestic market.

Early literature on international trade (e.g., Helpman and Krugman, 1989) suggests that the trade barriers reduce import competition – the unexpected reductions of trade barriers allow the foreign rival companies (to) enter the local market as an import penetration, as a result triggering an intensification of firms' competitive environment (Bernard, Jensen, and Schott, 2006; Valta, 2012). The import tariffs are widely recognized as effective trade barriers (Xu, 2012) and the reduction of the import tariffs represents the sharp exogenous shifts in the competitive pressure that U.S. companies face from their foreign rivals (Flammer, 2015). The entrance of the foreign rival companies increases the market competition for the domestic firms due to the sudden and substantial import tariff cuts. Following previous literature (e.g., Frésard, 2010, Xu, 2012, Valta, 2012, Flammer, 2015), we use the import tariff cuts for the U.S. IT industry as the exogenous shock and quasi-experiments to further examine the market competitions' impact on the innovations of the IT industry.

Previous literature (Griliches, Pakes, and Hall, 1988; Cornaggia et al., 2015) shows that the patent data are good proxies of the firm-level innovations. The number of a firm's total number of patents filed (and eventually granted) in a given year and the number of non-self citations per firm are two measures assessing the quantity and quality of the firms' innovations. Both measures are calculated from the National Bureau of Economic Research (NBER) Patent Citation database, which records all the patents registered and granted by the United States Patent and Trademark Office (USPTO), for both product and process innovations. The database includes such details as the corresponding patent assignee names, application and grant year of the patent, the record number and the number of citations for every patent in the USPTO records.

In this study, we utilize a comprehensive dataset to study the causal relationship between the product market competition and firms' innovations among U.S. public firms in the IT industry

from 1974 to 2005. We empirically examine the causal effects of the market competitiveness on the firm-level innovations. The findings suggest that the increased competition has a positive effect on IT innovations. To further address the endogeneity concerns, we apply the difference-in-differences (DID) method to conduct the robustness test. Specifically, after the exogenous shock to the market (industry competition increase due to import tariff cut), the number of patents per IT firm increases by 27.3%, and the number of non-self citations per IT firm increases by 38.2% on average. We also find that the positive effects are more pronounced in the more competitive sectors among all the IT firms.

Our research contributes to the Information Systems literature in three respects. First, we cleanly document a positive causal relationship between the market competition and firm-level innovations; that is, a fiercer competition leads to a better output of the firms' innovations. This research, to the best of our knowledge, is among the first to address the causality issue by natural experiments of the product market competition.

Second, prior studies have mainly focused on the relationship between competition and innovation in the manufacturing industry (e.g., Aghion et al., 2005; Hashmi, 2013). In this study, we focus on the hyper-competitive IT industry (Lee et al., 2010). Innovation enabled by IT investments is especially valuable in turbulent environments (Pavlou and El Sawy, 2010). Since innovation is the lifeblood of technology firms, our results highlight the importance of competition in the IT industry. In particular, the positive effect of competition on innovation in our context is likely to be driven by the *parallel search effect*, which is prominent in the IT industry (Boudreau et al., 2011; Zhang et al., 2019): multiple independent competitors compete to solve similar innovation problems. The parallel search effect increases with the degree of competition, which is

also consistent with our finding that the positive effect of the competition is more pronounced in the more competitive sectors among all the IT firms.

Third, our research has policy implications for trade induced innovations. A recent political debate is in progress over the impact of tariff wars[1] and protectionism (e.g., the possibility of withdrawing from the North American Free Trade Agreement[2]) on the U.S. economy. Our results suggest that increased import competition (import tariff cut) can induce faster firm-level innovations in the IT industry of the domestic market. In terms of trade policy, our results imply that reducing import barriers may bring important welfare gains through IT innovations. A caveat is that our empirical analysis focuses on the IT industry and does not capture all of the complex welfare effects of trade.

Literature Review

In this section, we review the literature from two different aspects: (i) competition and innovation in different industries, (ii) exogenous variations in market competition, and (iii) information technology strategies. We highlight our contributions by comparing and contrasting our work with past studies.

Competition and Innovation in Different Industries

Extant studies have examined the impact of competition on innovation and research and development (R&D) in various industries. van Cuilenburg and Slaa (1995) find that competition in the telecommunications industry stimulates innovation. As mentioned earlier, Aghion et al. (2005) find an inverted-U relationship between competition and innovation in the manufacturing industry.

[1] See https://www.bbc.com/news/world-43512098 (last accessed: August 15, 2020).
[2] See https://www.nytimes.com/2017/10/12/business/economy/what-would-happen-if-the-us-withdrew-from-nafta.html (last accessed: August 15, 2020).

Bos et al. (2013) present evidence of an inverted-U relationship between competition and innovation in the industry of financial services. Prior empirical literature suggests that there is no consensus about the effect of the competition on innovations. For instance, Blundell et al. (1999) show a positive relationship between competition and innovation spending. Kim et al. (2016) document a positive relationship between the competition and corporate venture capital (CVC) investment. However, Tang (2006) finds that the relationship is negative. Khan (2017, 2018), which are from antitrust law perspectives, argue that giant IT platforms are experiencing flagging competition in corresponding sectors, and the corresponding enhanced market power can manifest as non-price harms such as diminished innovations. In addition, Cornaggia et al. (2015) show that banking competition reduces state-level innovation by public corporations. However, innovation increases among private firms that are dependent on external finance and that have limited access to credit from local banks. Our research focuses on examining the causal impact of competition on innovation in the IT industry.

Exogenous Variations in Market Competition

The key of establishing the causal effect of competition on innovation is to find exogenous variations in market competition. Carlin et al. (2004) use the shift of transition economies from an economic system without competition to a market economy as an exogenous variation in market competition. Aghion et al. (2005) exploit exogenous policy shock, such as the introduction of the European Single Market Program. Xu (2012) uses two instrumental variables related to trade barrier reductions to capture exogenous variations in import competition: one is the import tariff reduction, and the other is the foreign exchange rates for import penetration. Hashmi (2013) adopts a trade-weighted average of industry exchange rates as an exogenous instrument. Valta (2012)

identifies 54 industries (in U.S. manufacturing sector) that experience large import tariff rate reductions between 1992 and 2005, and further examines the impacts on the firm-level costs of debt. Bloom et al. (2016) study the barrier reductions to Chinese imports as the exogenous instruments. We use import tariff cut as an exogenous variation in market competition because prior literature has shown that increased foreign imports can increase the level of competition in domestic product markets (Frésard, 2010).

Information Technology Strategies

Our paper is also related to firms' IT strategies. Based on 127 bank survey responses, Floyd and Wooldridge (1990) study the competitive strategy on IT and organizational performance. Karimi et al. (1996) discuss the firms' competitive strategy and IT maturity when experiencing the globalization of competition. Particularly, firms' perceived increase in IT investment and IT integration becomes their primary strategic response to globalization. Ravichandran et al. (2005) argue that the firms are using IT to support and enhance their core competencies, further impact firm performance. Kearns and Sabherwal (2006) and Wang et al. (2012) study the strategic alliance with IT and resource structuring on business value creation. Clemons et al. (2017) introduce the information-based transformation of strategy. Winkler and Wulf (2019) consider the IT service management's impact, while Kitchens et al. (2018) discuss the big data analytics' impact on the corresponding strategic value creation. Ding et al. (2017), Goh, Heng and Lin (2013) and Jin et al. (2020) state the importance of the IT strategies on social media activities using box office, fan page brand community and crowdfunding as examples. Soh and Grover (2020) focus on the mobile platform innovations and App innovations, and study the inter-relationship between these two innovations for developer and platforms' strategies. McKnight et al. (2020) further consider the

trust relationship and trust change, and their impacts on IT products and corresponding launch strategies. Cui et al. (2020) find that the IT-enabled inter-firm knowledge capabilities can effectively enhance collaborative innovations. Our study presents the empirical findings that the firms enhance their IT innovations as the strategic responses to the increased market competitions due to the import tariffs cut.

Data and Measures

Data

We construct our sample based on the U.S. public firms in the IT industry from several sources, including the innovation data, firms' characteristics data, and tariff data from 1974 to 2005.[3] Throughout this paper, we define the IT firms based on the Standard Industrial Classification (SIC, hereafter). Specifically, the sample contains the Hardware industry (first two-digit SIC code: 35), the Software industry (first two-digit SIC code: 36), and the computer-related Business Service industry (first three-digit SIC code: 234).

The innovation data comes from the NBER Patent Citation database, and we use the patent data as the proxy of the firms' innovativeness. The firms' characteristic data are from the Compustat database and the Center for Research in Security Prices (CRSP) database. The tariff data is from Schott's International Economics Recourse Page,[4] Trade Data, and Concordances. The import tariff rates are defined as the duties collected at U.S. Custom divided by the Free-On-Board custom value of imports at the three-digit SIC industry. And the tariff cuts are further defined as the situation in which the import tariff rate is three times larger than the median tariff reduction in the

[3] Because of the data availability on innovations (the NBER database covers from 1976 to 2006) and innovation measures definitions, we select the sample from 1974 to 2005 (we need at least one year data from the consecutive three year patent application procedure). A detailed introduction of the NBER database and measure definitions are further provided in Section 3.2.

[4] See http://faculty.som.yale.edu/peterschott/sub_international.htm (last accessed: August 15, 2020).

three-digit SIC sector (Frésard, 2010; Valta, 2012). The import tariff cuts invite foreign competition and thus increased product market competition in the U.S. domestic market.[5]

We merge all the above-mentioned data, and the final sample contains 514 firms in total. Table 1 discusses the variable definitions and the corresponding sources of data.

Table 1. Variable Definitions

Variable	Definition *(Compustat data codes are italicized)*
$LnPatents_{i,t+3}$	Natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year *t+3*
$LnCitations_{i,t+3}$	Natural logarithm of one plus firm *i*'s total number of non-self citations received on the firm's patents filed (and eventually granted) in year *t+3*
HHI	Herfindahl index, calculated as the sum of squared market shares of all Compustat firms in each four-digit SIC industry, and higher values indicate greater concentration and lower product market competitiveness.
Firm size (SIZE)	Log of the book value of total assets (*at*). Source: Compustat
Firm age (AGE)	Natural logarithm of one plus the number of years the firm is listed with a non-missing stock price from CRSP. Source: CRSP
Tobin's Q (Q)	Market value of assets over book value of assets: (*at* − *ceq* + *csho* × *prcc_f* - *txdb*)/*at*. Source: Compustat
Tangibility (PPE)	Property, plant, and equipment (*ppegt*) divided by total assets. Source: Compustat
Leverage (LEV)	Long-term leverage, defined as long-term debt (*dltt*) divided by total assets (*at*). Source: Compustat
ROA	Return on assets, measured as operating income (*pi* - *xi*) divided by lagged assets. Source: Compustat
Capex/Asset (CAPA)	Capital expenditure (*capx*) scaled by book value of total assets (*at*). Source: Compustat
R&D/Sales (RDS)	Research and development (R&D) expenditure (*xrd*) divided by sales (*sale*), set to 0 if missing. Source: Compustat
Cash holdings (CASH)	Cash and short term investments (*che*) divided by total assets (*at*). Source: Compustat

[5] The setting has been used by the recent literature. For instance, using a similar setting, Frésard (2010) investigates the causal impact of cash on product market performance.

Tariff	Duties collected at U.S. Custom divided by the Free-On-Board custom value of imports at the three-digit SIC industry. Source: Peter Schott's website http://faculty.som.yale.edu/peterschott/sub_international.htm.
Cut	Indicator variable coded as one if the reduction in the import tariff rate is 3 times larger than the median tariff reduction in the four-digit SIC industry, and zero otherwise.

Note : This table discusses the variable definitions and the corresponding sources of data.

Key Measures for Innovations

The NBER Patent Citation database records all the patents which are registered and granted by the United States Patent and Trademark Office (USPTO), for both product and process innovations during the time period from the year 1976 to 2006. The details include the corresponding patent assignee names, application and grant year of the patent, the record number, and the number of citations for every patent in the USPTO records.

We construct the key measures for firm-level innovations based on the number of patents and non-self citations. The number of a firm's total number of patents filed (and eventually granted) in a given year is calculated as the first measure. We utilize the application year in the firm-year observations because the application year captures the actual time of innovations (Griliches et al., 1988). However, the number of patents can only count the quantity of innovations and is significantly biased for the firm size. To overcome the shortcomings of the first measure, the number of non-self citations per firm is utilized as the second measure, which assesses the quality and the impact of a patent. These two measures of innovations can provide us insights into a firm's innovation from both the quantity and quality perspectives.

We further correct for two truncation issues with the corresponding innovation database (Hall et al., 2001). First, we apply the "weight factor" computed from the application-grant empirical distribution to correct for the end of the sample period truncation bias – the number of

patents filed (and eventually granted) will significantly decline in the last two to three years in our data sample because usually, it takes several years from the patent application to finally being granted[6]. Second, we utilize the shape of the citation-lag distribution to recover the possible non-self citations since, again, it takes time to generate citations for a patent. As the NBER patent database ended in 2006, we supplement it with information from the Harvard Business School (HBS) patent database and Kogan et al. (2012), which cover patents granted through 2010. This enables the calculation of citations for patents granted toward the end of the sample.

Notice that innovation is a long-term process. Therefore, in our empirical study, we focus on the number of patents and non-self citations over the next three years.[7] In the robustness tests, we also conduct further studies based on the number of patents and non-self citations over the next four and five years. Since both measures are nonnegative and significantly right-skewed, we take the log transformation of the number of patents (i.e., $LnPatents_{i,t+3}$), and the number of non-self citations per patent (i.e., $LnCitation_{i,t+3}$) in the empirical study.

Table 2. Summary Statistics and Correlation Table

Panel A: Summary Statistics

	Mean	Std.	Q1	Median	Q3	N
$LnPatents_{i,t+3}$	2.795	1.649	1.386	2.398	3.807	3,906
$LnCitations_{i,t+3}$	4.614	2.270	3.045	4.615	6.120	3,906
HHI	0.257	0.174	0.129	0.206	0.348	3,906
Firm size (SIZE)	5.945	1.909	4.609	5.760	7.188	3,906
Firm age (AGE)	2.357	1.006	1.609	2.485	3.178	3,906
Tobin's Q (Q)	2.095	3.039	0.741	1.279	2.341	3,906
Tangibility (PPE)	0.236	0.141	0.126	0.210	0.326	3,906
Leverage (LEV)	0.148	0.148	0.015	0.109	0.239	3,906

[6] The truncation bias happens from 2004 to 2006 because it is unknown that whether a filed patent application would be granted or not – thus we use the weight factors to fix this issue. We calculate the percentage of the filed patent applications granted over the total number of filed patents as the weight factor using the data from year 1976 to 2003 – then multiply the total patent applications by the weight factor to adjust the truncation bias for year 2004 to 2006.
[7] Lead 3 years measures are commonly used in the literature (e.g., Cornaggia et al., 2015).

ROA	0.037	0.193	-0.01	0.075	0.143	3,906
Capex/Asset (CAPA)	0.078	0.062	0.034	0.061	0.103	3,906
R&D/Sales (RDS)	0.095	0.074	0.044	0.081	0.125	3,906
Cash holdings (CASH)	0.247	0.201	0.079	0.200	0.365	3,906

Panel B: Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$LnPatents_{t+3}$	1.00											
$LnCitations_{t+3}$	0.79	1.00										
HHI	-0.01	0.02	1.00									
Firm size (SIZE)	0.73	0.44	0.05	1.00								
Firm age (AGE)	0.26	0.19	0.14	0.39	1.00							
Tobin's Q (Q)	0.06	0.03	-0.07	-0.08	-0.25	1.00						
Tangibility (PPE)	0.13	0.24	-0.11	0.03	0.18	-0.19	1.00					
Leverage (LEV)	-0.01	0.03	0.07	0.06	0.14	-0.25	0.30	1.00				
ROA	0.14	0.22	0.04	0.20	0.09	0.04	0.01	-0.17	1.00			
Capex/Asset (CAPA)	0.10	0.25	-0.10	-0.03	-0.10	0.00	0.69	0.08	0.11	1.00		
R&D/Sales (RDS)	-0.04	-0.04	-0.18	-0.23	-0.22	0.19	-0.12	-0.19	-0.46	0.00	1.00	
Cash holdings (CASH)	-0.05	-0.18	-0.18	-0.10	-0.36	0.34	-0.49	-0.42	-0.09	-0.25	0.24	1.00

Note: This table gives reports the summary statistics and correlation table. Panel A reports the summary statistics for variables constructed based on the sample of U.S. public firms in IT industry from 1974 to 2005. Panel B reports the correlation table.

Summary Statistics

Panel A of Table 2 provides the summary statistics for variables used in the empirical study. The average log number of patents ($LnPatents_{t+3}$) and non-self citations per patent are 2.795 and 4.614 per firm over the next three years in our sample, respectively, which translates to 16 patents and 101 citations per firm over the next three years. The Herfindahl-Hirschman Index (HHI, hereafter), defined as the sum of squared market shares of all Compustat firms in each four-digit SIC industry, is a proxy for the industry concentration and product market competitiveness. A higher value in HHI indicates a greater industry concentration and lower product market competitiveness (Herfindahl, 1964), and the average value of HHI is 0.257, with a standard deviation of 0.174. The

variation of HHI provides the possibility to explore its effects on firm-level innovations as the baseline analysis.[8]

The summary statistics of the firm characteristics are as follows. The average firm age is 11.6 years, and the average size is 382 million USD based on the book value of the total asset. Panel B of Table 1 also reports the average Tobin's Q (2.393), Tangibility (0.236), Leverage (0.148), Return on Asset (0.037), Capex/Asset (0.078), R&D/Sales (0.095) and the Cash holdings (0.247). The standard deviations and several quantiles are also included in Table 2 Panel A.

Table 2 Panel B reports the correlation table of the variables utilized in this paper: the correlation between two innovation measures are quite high (0.79), which shows that though the quantitative and qualitative innovation measures are from different perspectives, usually the number of patents and non-self citations per patent co-move on the same direction. The correlation between the innovation measures and firm size is large (0.73 and 0.44, respectively), which shows that the innovation measures are significantly affected by the firm size measures. Note that the correlations between HHI and LnPatents_{t+3} (LnCitations_{t+3}) are relatively weak – after controlling the size effect, the residual terms of LnPatents_{t+3} (LnCitations_{t+3}) are negatively correlated with HHI.

Empirical Results

Baseline Analysis

In this section, we study the relationship between the market competitiveness and the innovations at the firm level using the following empirical models.

(1)

[8] The HHI index is calculated based on 4-digits SIC code, and the industry is based on 2-digits or 3-digits SIC code. Therefore, there are variations of HHIs within an industry.

where is $LnPatents_{i,t+3}$ or $LnCitation_{i,t+3}$, is the Herfindahl-Hirschman Index of the industry to which firm *i* belongs at year , is the vector of the remaining control variables, including *Size, Age, Q, PPE, LEV, ROA, CAPA, RDS* and *CASH*. and are the corresponding time and firm fixed effects. We also control the clustering at the firm level using the heteroscedasticity-consistent standard errors.

Table 3 reports the baseline regression of the effect of market competition on innovation outcome variables. The coefficients of are -0.840 (Model 2) and -1.124 (Model 4) for $LnPatents_{i,t+3}$ and $LnCitation_{i,t+3}$ as the dependent variable, respectively. Both are negatively statistically significant and the overall are as high as 0.859 and 0.841. Note that the higher the , the lower the competitiveness within the industry, and the significant negative coefficients of indicate that firm innovation increases with the competitiveness within the industry. Specifically, one standard deviation higher in (0.174), will result in 14.62% (0.840*0.174) lower in the number of patents, and 19.56% (1.124*0.174) lower in the number of non-self citations per firm over the next three years. Intuitively, one standard deviation higher in HHI means that we compare firms in the 84^{th} and 50^{th} percentile of the ranked competitiveness of the industry. Roughly speaking, the number of patents of a firm in the 84^{th} percentile is 14.62% lower than that of a firm in the 50^{th} percentile.

These results provide empirical evidence on the positive relationship between industry competitiveness and IT firm-level innovations. In other words, greater competition will lead to a higher level of IT innovations, from both the quantity and quality perspectives. We further conduct the robustness check using the scaled innovation measures (the two measures are the logarithms of the number of patents ($LnPatents_{t+3}$) and non-self citations per patent scaled by firm total assets), or alternative measures which combine both quantitative and qualitative measures (using the

principal component analysis to obtain the first principal component), and the findings are consistent and robust.

Table 3. Baseline Regression of Innovation Outcomes on Product Market Competition

	$LnPatents_{i,t+3}$		$LnCitations_{i,t+3}$	
	(1)	(2)	(3)	(4)
HHI	-0.240**	-0.840***	-0.506***	-1.124***
	(-2.229)	(-4.982)	(-3.385)	(-4.505)
Firm size (SIZE)	0.718***	0.450***	0.781***	0.439***
	(66.94)	(14.88)	(55.10)	(10.11)
Firm age (AGE)	0.0241	-0.115**	0.0276	-0.164**
	(1.217)	(-2.433)	(0.953)	(-2.264)
Tobin's Q (Q)	0.0548***	0.0222***	0.0780***	0.0279***
	(6.421)	(4.746)	(6.309)	(3.970)
Tangibility (PPE)	1.435***	0.891***	1.310***	1.527***
	(6.866)	(3.620)	(4.680)	(4.061)
Leverage (LEV)	-0.362***	-0.371***	-0.349*	-0.234
	(-2.684)	(-2.857)	(-1.894)	(-1.248)
ROA	0.0524	0.272**	0.181	0.525***
	(0.454)	(2.490)	(1.075)	(3.423)
Capex/Asset (CAPA)	0.592	-0.501	1.820***	-0.637
	(1.475)	(-1.436)	(3.240)	(-1.252)
R&D/Sales (RDS)	3.252***	1.379***	4.393***	1.777***
	(11.23)	(3.510)	(10.15)	(3.048)
Cash holdings (CASH)	0.701***	0.129	1.045***	0.298*
	(6.084)	(1.061)	(6.401)	(1.657)
Constant	-1.650***	-0.792***	0.388**	0.515
	(-12.66)	(-4.002)	(2.113)	(1.467)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes
Observations	3906	3906	3906	3906
Adjusted R2	0.631	0.859	0.628	0.841

Note: This table presents the baseline results of the effect of product market competition on innovation outcome variables (three-year-ahead number of patents and number of non-self-citations). T-stats based on the heteroscedasticity-consistent standard errors clustered at the firm level are reported in brackets.
*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Controlling for Endogeneity: Natural Experiment

Though the baseline analysis provides empirical evidence, the endogeneity issue is the key concern in ascertaining the conclusion that stronger competition leads to increased innovations in the IT industry. In order to address the endogeneity concern, we further examine the effect based on natural experiments: the import tariff cuts. The import tariff cuts invite increased foreign competition and thus greater product market competition in the U.S. domestic market.[9] Throughout this section, a tariff cut is defined to occur if the reduction in the import tariff rate is three times larger than the median tariff reduction in the three-digit SIC sector (Frésard, 2010; Valta, 2012). We apply the DID method to assess the relationship between the exogenous shocks to product market competition caused by import tariff cuts and firm-level innovations.

Table 4. DID Test Results

Panel A. Summary Statistics for Matched Samples prior to Tariff Reductions

Variable	Treated Firms			Matched Control Firms			Difference in Means	T-Stat.
	Mean	Std.	Med.	Mean	Std.	Med.		
SIZE	4.088	1.991	3.828	4.308	2.296	3.745	-0.220	[-1.06]
Q	2.073	1.485	1.562	1.879	1.476	1.616	0.194	[1.36]
RDS	0.087	0.077	0.068	0.083	0.070	0.071	0.004	[0.53]
ROA	0.049	0.206	0.096	0.057	0.215	0.112	-0.008	[-0.40]

Panel B. DID Results for Year *t+3* vs. *t-3*

	Average Treated Difference (year *t+3* vs. *t-3*)	Average Control Difference (year *t+3* vs. *t-3*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.102**	-0.171***	0.273***
	[0.051]	[0.048]	[0.070]
LnCitations	-0.037	-0.419***	0.382***
	[0.096]	[0.083]	[0.127]

Panel C. DID Results for Year *t+4* vs. *t-4*

[9] The setting has been used by the recent literature. For instance, using a similar setting, Frésard (2010) investigates the causal impact of cash on product market performance.

	Average Treated Difference (year *t+4* vs. *t-4*)	Average Control Difference (year *t+4* vs. *t-4*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.131**	-0.184***	0.315***
	[0.056]	[0.054]	[0.078]
LnCitations	-0.034	-0.444***	0.410***
	[0.099]	[0.089]	[0.134]

Panel D. DID Results for Year *t+5* vs. *t-5*

	Average Treated Difference (year *t+5* vs. *t-5*)	Average Control Difference (year *t+5* vs. *t-5*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.148**	-0.195***	0.343***
	[0.060]	[0.059]	[0.084]
LnCitations	-0.038	-0.467***	0.428***
	[0.103]	[0.094]	[0.139]

Note: This table reports diagnostics and results of the DID tests on how exogenous shocks to product market competition (import tariff reductions) affect firm innovation activities. Panel A reports the univariate comparisons between treatment and control firms' characteristics and their corresponding t-statistics. Panels B, C, and D give the DID test results for year *t+3* vs. *t-3*, year *t+4* vs. *t-4*, and year *t+5* vs. *t-5*, respectively. Heteroscedasticity-consistent standard errors are reported in brackets unless specified.
*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4 reports the diagnostics and results of the DID tests on how exogenous shocks to product market competition (due to import tariff reductions) affect the IT firm innovation activities. The sample begins with all firm-years in IT industry from 1974 to 2005 with non-missing matching variables and non-missing innovation outcome variables during a seven/nine/eleven-year window (from year −3 to year +3/ from year −4 to year +4/ from year −5 to year +5) around the actual or matched event year. The sample consists of 216 treated firms that experience a significant import tariff reduction between 1989 and 2005, and the same number of control firms.

Control firms are a subset of the non-treated firms selected as the closest match to the treated firms in the year before the tariff reduction based on a set of firm characteristics: size, Tobin's Q, R&D/sales, and ROA. Both groups of firms are publicly traded U.S. IT firms. Essentially, our approach is a DID model combined with propensity score matching (PSM).

Following Bapna et al. (2019), Cheng et al. (2020), Goh et al. (2013), Li (2016), Khurana et al. (2019), Kumar et al. (2018) and Xie et al. (2020), we ensure that the control and treated groups are comparable in terms of observable characteristics. Then, we run the DID regression equation.

It is worth noting that the traditional PSM takes care of only *observable* characteristics and may be biased in the case of selection-on-unobservables (Mithas and Krishnan 2009). However, in the implementation of the DID approach combined with PSM, even if treated units differ in important *unobserved* characteristics from those in the control group, so long as such differences between the control and treatment groups are stable over time in their influence on innovation, our specification can eliminate the bias resulting from the differences between treated units and control units. On the other hand, the traditional DID approach relies on the strong "parallel paths" assumption. If the violation of the "parallel paths" assumption is caused by the differences in observable characteristics, augmenting DID with PSM is an effective method to correct the possible bias.

Panel A of Table 4 reports the univariate comparisons between treatment and control firms' characteristics and their corresponding *t*-statistics. And the insignificant difference between the treatment group and control group shows the similarity of the two groups in terms of the firm characteristics and the feasibility to conduct the DID and suggests that matching helps reduce the bias associated with the observable characteristics.

Panel B of Table 4 reports the DID results for year vs. and the coefficients are 0.273 and 0.382 for the number of patents and non-self citations, respectively, both statistically significant. The positive number suggests that after the tariff cut, i.e., an increase of market competitiveness, the innovation of the IT firm is improved, from both the quantity (*LnPatents*) and the quality (*LnCitation*) perspectives. Specifically, after the exogenous shock to the market competitiveness

(import tariff cut and thus the industry competition increase), the number of patents per IT firm increases by 27.3%, and the number of non-self citations per IT firm increases by 38.2% on average. We find consistent evidence from DID analysis for year vs. and vs. in Panels C and D of Table 4.

Robustness Test: Alternative Matching Criteria & Alternative Thresholds

The baseline analysis and the DID analysis provide a consistent empirical conclusion: the competition has a positive effect on the IT firms' innovation activities. In this subsection, we provide more evidence based on alternative matching criteria to examine the robustness of the treatment effect caused by the natural experiment, and the findings are insensitive to the matching schemes with different control variables. Five different matching schemes are implemented in this test, and the results can be found in Table 5:

1. Naïve-matched,
2. SIZE/RDS/LnPatentst-3/ LnCitationst-3-matched,
3. SIZE/RDS/ROA-matched,
4. SIZE/Q/RDS/ROA/PPE/CASH-matched, and
5. SIZE/AGE/Q/RDS/ROA/PPE/LEV/CASH/CAPA-matched.

Following the same treatment group in the previous section, 216 treated firms that experience a significant import tariff reduction between 1989 and 2005 are included in the treatment group, and the same number of control firms are included in the control group under different matching schemes. Table 5 reports the DID coefficients for the robustness tests of the DID tests, which are consistent with the previous DID results. We firstly try naïve matching without using these variables, and the results are similar, except the estimates for 3-year measure is

slightly lower and less significant than the baseline DID results. We try matching using firm size, R&D/sales, and past 3-year average patents and citations, and we find similar results compared to our baseline DID results. We then try adding ROA, tangibility, leverage, Tobins' Q, firm age, capital expenditure, and cash holdings step by step. Finally, we repeat the matching procedure by including all the available matching variables. All of the DID results are qualitatively similar, implying that our findings are robust to various matching methods.

Next, we implement the alternative thresholds as the additional robustness check: a significant import tariff reduction is defined if the reduction in the import tariff rate is 4 times (Panels A, B, and C) and 5 times (Panels D, E, and F) larger than the median tariff reduction in the four-digit SIC industry. Control firms are a subset of the non-treated firms selected as the closest match to the treated firms in the year before the tariff reduction based on a set of firm characteristics: size, Tobin's Q, R&D/sales, and ROA. The results are reported in Table 6, and we find consistent and robust empirical results.

Therefore, we conclude that the findings that the exogenous shocks to competition (import tariff reductions) affect the IT firm innovation activities are robust, and more specifically, the competition has a robust positive effect on the IT firms' innovation from both baseline analysis (index) and natural experiment approach.

Table 5. Robustness Tests for DID Analysis: Alternative Matching Criteria

	Year *t+3* vs. *t-3*		Year *t+4* vs. *t-4*		Year *t+5* vs. *t-5*	
	LnPatents	LnCitations	LnPatents	LnCitations	LnPatents	LnCitations
	(1)	(2)	(3)	(4)	(5)	(6)
Naïve-matched	0.081	0.151	0.105*	0.178*	0.125**	0.194*
	[0.050]	[0.095]	[0.055]	[0.099]	[0.059]	[0.102]
SIZE/RDS/LnPatents$_{t-3}$/ LnCitations$_{t-3}$-matched	0.149*	0.241*	0.179**	0.265*	0.203**	0.278*
	[0.082]	[0.146]	[0.091]	[0.153]	[0.098]	[0.159]
SIZE/RDS/ROA-matched	0.176**	0.324**	0.220**	0.356**	0.249**	0.376**
	[0.090]	[0.162]	[0.100]	[0.171]	[0.108]	[0.177]
SIZE/Q/RDS/ROA/PPE/CASH-matched	0.183**	0.329**	0.214**	0.360**	0.239**	0.380**
	[0.084]	[0.154]	[0.094]	[0.163]	[0.102]	[0.171]
SIZE/AGE/Q/RDS/ROA/PPE/LEV/CASH/CAPA-matched	0.206**	0.265*	0.245***	0.304*	0.270***	0.325*
	[0.086]	[0.156]	[0.094]	[0.164]	[0.101]	[0.170]

Note: This table reports robustness tests of the DID tests on how exogenous shocks to product market competition (import tariff reductions) affects firm innovation activities, using alternative matching criteria. Heteroscedasticity-consistent standard errors are reported in brackets unless specified.
*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6. DID Tests Using Alternative Thresholds as Shocks

Panel A. DID Results for Year *t+3* vs. *t-3* (4 Times Tariff Reduction)

	Average Treated Difference (year *t+3* vs. *t-3*)	Average Control Difference (year *t+3* vs. *t-3*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.168***	-0.063	0.231***
	[0.046]	[0.046]	[0.065]
LnCitations	-0.028***	-0.250***	0.223***
	[0.006]	[0.006]	[0.008]

Panel B. DID Results for Year *t+4* vs. *t-4* (4 Times Tariff Reduction)

	Average Treated Difference (year *t+4* vs. *t-4*)	Average Control Difference (year *t+4* vs. *t-4*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.269***	0.019	0.250***
	[0.052]	[0.053]	[0.074]
LnCitations	-0.021***	-0.315***	0.294***
	[0.007]	[0.007]	[0.010]

Panel C. DID Results for Year *t+5* vs. *t-5* (4 Times Tariff Reduction)

	Average Treated Difference (year *t+5* vs. *t-5*)	Average Control Difference (year *t+5* vs. *t-5*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.454***	0.078	0.376***
	[0.059]	[0.060]	[0.084]
LnCitations	-0.018**	-0.365***	0.347***
	[0.008]	[0.008]	[0.011]

Panel D. DID Results for Year *t+3* vs. *t-3* (5 Times Tariff Reduction)

	Average Treated Difference (year *t+3* vs. *t-3*)	Average Control Difference (year *t+3* vs. *t-3*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.164***	-0.163***	0.327***
	[0.057]	[0.056]	[0.080]
LnCitations	-0.037***	-0.255***	0.218***
	[0.007]	[0.008]	[0.010]

Panel E. DID Results for Year *t+4* vs. *t-4* (5 Times Tariff Reduction)

	Average Treated Difference (year *t+4* vs. *t-4*)	Average Control Difference (year *t+4* vs. *t-4*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.265***	-0.108*	0.372***
	[0.065]	[0.064]	[0.091]
LnCitations	-0.032***	-0.321***	0.289***
	[0.008]	[0.009]	[0.012]

Panel F. DID Results for Year *t+5* vs. *t-5* (5 Times Tariff Reduction)

	Average Treated Difference (year *t+5* vs. *t-5*)	Average Control Difference (year *t+5* vs. *t-5*)	Diff-in-Diffs (Treated vs. Control)
LnPatents	0.412***	-0.098	0.510***
	[0.073]	[0.074]	[0.103]
LnCitations	-0.034**	-0.375***	0.342***
	[0.010]	[0.010]	[0.014]

Note: This table reports diagnostics and results of the DID tests on how exogenous shocks to product market competition (import tariff reductions) affect firm innovation activities. A significant import tariff reduction is defined if the reduction in the import tariff rate is 4 times (Panels A, B, and C) and 5 times (Panels D, E, and F) larger than the median tariff reduction in the four-digit SIC industry. Heteroscedasticity-consistent standard errors are reported in brackets unless specified.
*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Subsample Analysis: Conditional on Market Structure prior to Import Tariff Cut

We further explore the performance among different types of market competitiveness. Conditional on the market structure prior to the import tariff cut, we classify the firms into two categories of high and low market competitiveness prior to the tariff cut based on and medians, and then study the performance in each group.

Table 7. Further Explorations of DID Analysis: Conditional on Product Market Structure Prior to Import Tariff Reductions

	Year *t+3* vs. *t-3*			
	HHI		Market Share	
	High	Low	High	Low
LnPatents	0.240***	0.305***	0.280**	0.185**
	[0.084]	[0.111]	[0.113]	[0.087]
LnCitations	0.259	0.503***	0.357*	0.265
	[0.161]	[0.191]	[0.194]	[0.173]

Note: This table reports further explorations of the DID tests on how exogenous shocks to product market competition (import tariff reductions) affect firm innovation activities, conditional on product market structure prior to import tariff reductions. We use two measures of market structure: HHI of the four-digit SIC industry and market share of the firm in the four-digit industry. Heteroskedasticity-consistent standard errors are reported in brackets unless specified.
*, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7 reports the empirical results of the DID tests, for high and low competitive sectors prior to the tariff cut. High and low of the firm in the four-digit SIC sectors correspond to the low market competitiveness, and *vice versa*. The effects of the natural experiments are more pronounced in terms of the economic magnitude for the more competitive sectors. Furthermore, the increased numbers of non-self citations after the tariff cut are statistically significant for the more competitive sectors, while we find corresponding insignificant results when is high, or is low in the four-digit SIC sectors (less competitive sectors). The empirical results suggest that the market structure prior to the import tariff cut plays an important role in deciding the impact of competition on innovations of the IT industry. In the more competitive sector, the effects are more pronounced, and the sudden increase in the competition after the tariff cut will result in a larger increase in innovations of the IT firms.

Conclusion and Discussions

In this paper, we document a robust causal relationship between product market competitiveness and innovations in the IT industry. The IT industry, which is widely regarded as an increasingly "knowledge intensity" industry (El Sawy et al., 1999) with the market competition as the systemic feature (McAfee and Brynjolfsson 2008), involves fast-moving technological progress; therefore, the firms in the IT industry have a strong incentive to respond to product market competition and keep their corresponding comparative advantages.

Utilizing the firm-level innovation data from both the quantity (number of patents) and the quality (number of non-self citations) perspectives, we find causal and robust evidence that competition has a positive impact on IT innovations. Specifically, after the exogenous shock to the market with the increase of industry competition from an import tariff cut, the number of patents per IT firm increases by 27.3%, and the number of non-self citations per IT firm increases by 38.2% on average. The effects are more pronounced in the more competitive sectors. Based on our data sample of more than thirty years, our findings are both statistically and economically significant. Our research identifies the determinants of the innovations and provides direct empirical evidence to demonstrate the firm-level innovative activities under the competitive environment. Our findings also provide empirical evidence and further shed light on the firms' IT strategies and R&D decisions when experiencing fiercer competitive market conditions.

A limitation of our study is the data availability as the NBER Patent Citation database only records all the patents that are registered and granted by the United States Patent and Trademark Office (USPTO) from 1976 to 2006. It will be of interest to replicate the study for other time periods should those data become available.

As discussed earlier, a recent political debate is in progress over the impact of tariff wars and protectionism on the U.S. economy. Typical arguments supporting protectionism are based on the assumption that restrictions, such as tariffs, can shield some of the home country's industries from foreign competition and help boost those industries. Our results suggest that increased tariffs can be detrimental to firm-level innovations. In contrast, increased import competition (import tariff cut) can induce faster firm-level innovations in the IT industry of the domestic market. In terms of trade policy, our results imply that reducing import barriers may bring important welfare gains through IT innovations. A caveat is that our empirical analysis focuses on the IT industry and does not capture all of the complex welfare effects of trade.

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