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Protect or Compete? Evidence of Firms' Innovation from Import Penetration

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Abstract: This paper reassesses the long-debated relationship between market competition and firms' innovation. While competition is traditionally measured at the industry level using historical data, our study utilizes two recently developed text-based measures of competitive threats which are forward-looking and constructed at the level of individual firms. We address the potential endogeneity concerns and provide causal inference using instrumental variables including import tariffs and trade-weighted exchange rates, along with the propensity score matching (PSM) of firms that experienced exogenous shock from import competition. Our results show that an increase in competition unambiguously promotes firms' innovation in terms of both quality and quantity.

Keywords: innovation; product market competition; patents; import penetration; import tariffs; exchange rates; text-based measures

JEL Classification: L10; O31

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1. Introduction

This paper revisits the long-debated relationship between product market competition and firms' innovation. On the one hand, the view that competition hinders innovation can be traced back to an early view proposed by Schumpeter (1942) that the presence of monopoly rents generates incentives for innovation, whereas perfect competition is not optimal for innovation (i.e., the Schumpeter effect). On the other hand, Arrow (1962) holds the alternative view that competition promotes innovation because a monopolist has a weaker incentive to innovate, since, by innovating, the monopolist merely replaces itself (i.e., the Arrow effect). More recent theories have taken a middle ground and attempted to reconcile the mixed arguments to arrive at a non-linear relationship.[1] It is no surprise that the prediction of theoretical models relies heavily on their underlying assumptions. On the empirical side, it is equally challenging to derive a causal relation between competition and innovation, due to the absence of a perfect proxy for competition and the innate endogeneity problem of such measures, since an increase in innovation per se affects the competitive landscape of the market. Gilbert (2006) concluded that the current literature was far from providing a general theory of innovation competition. Our paper empirically re-examines this much-debated relation by directly documenting evidence of causal inference between product market competition and innovation, which could provide valuable policy implications.

While it is admittedly impossible to reconcile all prior literature in a single setting, we aim to provide causal evidence from a new perspective for competition and innovation at the firm level. Traditional measures of market competition such as the Herfindahl index (HHI) and concentration ratio (CR) are calculated at the industry level. Gilbert (2006) reported that prior empirical studies using such industry-level measures did not arrive at a robust conclusion. It is likely that firms, although in the same industry, face different levels of threats depending on their unique competitive positions. Applying a generalized measure across all firms in the same market may eliminate very important variations. Therefore, we reassess this controversial relationship between market competition and firms' innovation by leveraging two newly developed firm-specific competitive threat measures constructed using computational linguistics, over a large sample of 10-K filings. We first examined the association between competitive threat and various innovation measures, using pooled ordinary least squares (OLS) regression. We found a consistent positive relation between competitive threat and firms' innovation activities. Our results bolster the argument that competition may force firms to develop new products through innovation, in order to gain competitive advantage. Empirically, a one-standard-deviation change in competition can result in an approximately 5.5% increase in the number of patent applications or a 4% increase in R&D intensity in an average firm. To address the potential endogeneity concerns related to omitted variable bias and reverse causality, we first employed import tariffs and exchange rates as our instrumental variables (IVs), and found that both arguably affect innovation only through competition. We also considered evidence from quasi-natural experiments by identifying sudden reductions in import tariffs as exogenous shocks to competition.[2] The results of the two-stage least squares (2SLS) regressions and propensity score matching (PSM) are strongly consistent with our OLS results. Our results also unambiguously suggest that firms under competition produce better quality innovation in terms of patent citations. Finally, an important insight from our study is that text-based competition measures can be utilized by regulators to evaluate firms' perceived competitive threats. This can be used as a strategic tool to monitor foreign trade risks and foster domestic innovation. Similarly, companies can also examine their rivals' perceived competitive threats and devise suitable strategies to enhance their own global business operations by identifying market gaps, exploring new business prospects, and creating innovative solutions that cater to changing consumer needs.

2. Literature Review

Innovation is generally considered a key determinant of a firm's performance and, consequently, its economic growth (Mulkay 2019). Therefore, numerous studies have attempted to identify the factors that drive firms' innovation. At the micro level, prior literature has documented that both firm-level and managerial level characteristics are critical to firms' innovation. These characteristics include but are not limited to ownership structure, financial dependence, corporate governance, CEO age, CEO narcissism, and CEO functional experience (Kortum and Lerner 2000; Acharya and Xu 2017; Balsmeier et al. 2017; Kashmiri et al. 2017; Saboo et al. 2017). However, a firm's level of innovation is not solely determined by internal factors, but is also greatly affected by the external economic environment in which the firm operates. Given that corporate innovation ultimately gives innovative firms a competitive edge in the product market, the influence of product market competition on corporate innovation has drawn considerable attention from researchers (He and Tian 2018).

The relationship between competition and innovation has long been theoretically and empirically studied by researchers. However, the extant literature has not reached a full consensus on the effects of competition on innovation. Theoretically, the debate traces back to Schumpeter (1942) and Arrow (1962). Schumpeter (1942) argued that competition negatively affects innovation. Specifically, monopoly rents generate incentives for innovation, whereas perfect competition is not the optimal market structure for innovation (i.e., the Schumpeter effect). On the other hand, Arrow (1962) proposed a positive relationship, stating that competition rather than monopoly encourages innovation. The main argument of Arrow (i.e., escaping competition effect) is that the monopolist gains little from additional innovation, because it has already captured most of the market, whereas a competitor has no pre-existing profit to replace. After the initial spark of the debate, many theoretical studies have drawn similar conclusions to those of Schumpeter (Gilbert and Newbery 1982; Greenstein and Ramey 1998; Chen and Schwartz 2013) or Arrow (Reinganum 1983;

Weinberg 1992). Following the prior theoretical foundations, a new strand of the literature emerged in an attempt to reconcile the two opposing conclusions and arrived at non-linear (e.g., inverted U shape) relationships (Schmidt 1997; Boone 2001; Aghion et al. 2005; Aghion and Griffith 2008; Hashmi 2013; Cornett et al. 2019). However, no unambiguous conclusion can be drawn as the theoretical relation between competition and innovation remains confounded by the complexity of market structures, innovation characteristics, and the dynamics of innovation discovery (Kamien and Schwartz 1975; Gilbert 2006).[3]

While no robust relationship exists between competition and innovation from the perspective of theory, empiricists have been striving equally hard to find real-world evidence but have provided no clearer answers. For instance, Scherer (1965) found no correlation between concentration ratio and R&D intensity, whereas Mansfield et al. (1977) documented only limited evidence of a positive correlation between market concentration and R&D expenditure, and none when concentration is above moderate levels. However, Angelmar (1985) concluded that such a positive correlation only applies in industries with low barriers to imitation and becomes negative in industries with high barriers to imitation. A survey study conducted by Gilbert (2006) provided a broad list of earlier empirical studies that reported positive, negative, no, or mixed relations between competition and innovation. Inevitably, early empirical research usually examined only correlations between market structure and innovation. Such studies are deemed uninformative, since they do not adequately control for technological opportunities that vary across industries and are correlated with traditional industry-level competition measures (Nickell 1996).

Although more researchers have tried to disentangle this relationship by applying new measures, recent results remain inconclusive. For example, Bloom et al. (2016) show that import competition from China can increase the R&D expenditure and patenting activities in twelve European countries. Similarly, Ahn et al. (2018) report positive effects of import competition from China on innovation for firms in South Korea. In the same vein, Bombardini et al. (2017) focus on Chinese manufacturing firms and reveal that increased import competition after China's accession to the WTO encouraged innovation, but only for productive firms. In contrast, in the same Chinese context, Liu et al. (2021) demonstrate a negative relationship between import competition and innovation by comparing industries with higher trade liberation and those with lower trade liberation. For US firms, according to a recent review on trade liberation and innovation by Shu and Steinwender (2019), the mixed results are even more pronounced. Specifically, Hashmi (2013) find a mildly negative relationship, Autor et al. (2020) document a significantly negative relationship, and Chakravorty et al. (2022) report a significantly positive relationship between competition and citation-weighted patents. Additionally, Aghion et al. (2018) employed two laboratory experiments to support the non-linear relationship.[4]

When it comes to interpreting empirical studies, the potential endogeneity between innovation and competition is always of great concern. The confounding relation is complex, and reverse causality is highly likely because conducting innovation per se changes the competitive landscape of a market. The simultaneous effects of competition and innovation make it difficult to obtain causal inferences for the effect of competition. Xu (2012) introduced the use of tariff rates and foreign exchange rates as IVs for import competition and found that competition significantly reduced expected profits and firms' leverage. We follow the approach taken by Xu (2012) to address the endogeneity problem by using import tariffs and foreign exchange rates as IVs for product market competition. This approach has also been adopted by researchers to study the effects of competition on stock price crash risk, corporate disclosure, and leverage adjustments (Huang et al. 2017; Li and Zhan 2019; Do et al. 2022).

Another challenge confronted by empiricists is the construction of a satisfactory measurement for market competition. Traditional competition measures such as HHI or the CR of the largest firms are embedded with several limitations. These measures are calculated at the industry level using historical data. The competitive threat faced by a firm may not fully be accounted for, since only sales data of public firms are available for most periods. Scherer (1986) reiterates that conclusions drawn from using traditional industry-level measures of the effects of competition on innovation may be merely an artifact of inadequate controls for differences in opportunities for R&D among firms and industries.

Borrowing from computational linguistics, Hoberg et al. (2014) constructed a new measure of product market threat at the firm level through textual analysis of a large sample of 10-K filing (i.e., *Fluidity*). They found that increasing product market competition reduces the likelihood of dividend payouts or share repurchases and that such firms hold more cash. Li et al. (2013) also developed a simple but novel measure of competition using 10-K filings (i.e., *Pctcomp*) and found that this new firm-level measure is only weakly related to traditional competition measures but can itself reconstruct an industry-level measure. They highlight that the new measure is generally useful for financial statement analysis. A significant improvement over the traditional measures is that *Fluidity* and *Pctcomp* are forward-looking and capture competitive threats from the managers' perspectives without being bound by the definition of industries.[5] Both measures are employed in our study, with a greater emphasis on the former which has also been more widely used in the prior literature.[6] For example, it was used to analyze the impact of product market competition on firms' choices between bank debt and private debt, corporate greenwashing, and corporate social responsibility disclosure (Boubaker et al. 2018; Arouri et al. 2021; Ryou et al. 2022).

Our paper contributes to the literature in several important ways. Firstly, we aim to augment the current debate surrounding the relationship between competition and innovation, by presenting new firm-level empirical evidence. Secondly, through our utilization of novel text-based measures, we are better able to capture the genuine competitive pressure facing individual firms from the perspective of their managers, in contrast to traditional industry-level measures with limited firm-level variations. Thirdly, we address the potential endogeneity issue and obtain causal inferences relating to the impact of product market competition on innovation. Finally, our findings have the potential to provide practical implications for firms to assess perceived threats from rivals, in order to devise appropriate strategies to prevent market overlap, as well as for policymakers in the design of foreign trade policies and anti-trust regulations aimed at fostering domestic innovation.

The remainder of the paper is organized as follows: Section 3 elaborates on the construction of variables and our empirical strategy; Section 4 shows and discusses the main empirical results; Section 5 provides the conclusion.

3. Materials and Methods

3.1. Measuring Competition

Traditional industry-level competition measures such as HHI and CRs are static and backward-looking, also ignoring the within-industry variation in competition at the level of firms (Li et al. 2013; Hoberg et al. 2014). Reliance on historical public sales data often neglects competition from private competitor firms, leading to poor proxies for actual industry concentration (Ali et al. 2008; Bens et al. 2011). To overcome the above limitations, we leverage the new measure, *Fluidity*, developed by Hoberg et al. (2014) using firms' 10-K filings. Intuitively, *Fluidity* captures the similarity (i.e., cosine similarity) between the word usage vector of a firm and the word usage vector that reflects rivals' actions. If there is a higher overlap between a firm's products and the changes in the competitors', then the firm is facing greater competition. This measure is obtainable from the Hoberg–Philips Data Library. We also use *Pctcomp* as an alternative measure of competition, as constructed by Li et al. (2013), for a robustness check.[7] *Pctcomp* measures the number of occurrences of competition-related words, which is an indication of the firm's competitive pressure from the managers' perspective. Both measures are firm-specific and are based on the textual analysis of management disclosures in 10-K filings, unlike the traditional measures that are calculated using primarily historical sales data at the industry level. The two measures are forward-looking rather than a market representation of the past, and they consider competitive threats from non-public firms, which constitute a significant portion of the product market.

3.2. Measure Innovation

We use R&D expenditures from the Compustat Database as a direct proxy for inputs to innovation. We also use the most recent patent database from Kogan et al. (2017), containing information on all patents granted by the US Patent and Trademark Office (USPTO) between 1926 and 2010. We focus on the number of patents filed and patents issued, as proxies for firms' innovation activity.

3.3. Addressing Endogeneity and Measurement Error

Empirical evidence from reduced-form regressions is usually plagued with endogeneity concerns. An omitted factor could be present that affects both competition and innovation, or a feedback loop may exist between innovation and competition since innovation itself can affect the competitive landscape of a product market. As emphasized by Aghion et al. (2018), it is difficult to find exogenous variation in competition measures and this difficulty can be coupled with the additional problem of measurement error. To address potential omitted variable bias or reverse causality, we follow Xu (2012) in the use of import tariffs and foreign exchange rates as instrumental variables for product market competition.[8]

Due to the availability of the import data, our IV regressions are restricted to firms in the manufacturing industry only. Li and Zhan (2019) have shown that this sub-sample of firms is not significantly different from other industries. We found that these two IVs satisfy the relevance condition, because they are highly correlated with the abovementioned competition measures. Import tariffs represent an important policy instrument for regulating competition from foreign firms. Lower import tariffs inevitably lead to heightened competition from abroad. Foreign exchange rates also affect the competitiveness of imported goods since cheaper foreign currency encourages imports. We use the updated version of import data, as in Schott (2008), and define the tariff rate as the total amount of general import charges divided by the total general import values of the US manufacturing sector.[9] For calculating the foreign exchange rate, we use the average yearly nominal exchange rate of all US trade partners weighted by the percentage value of their yearly imports for each 3-digit SIC industry in every year.[10] All exchange rate data were obtained directly from the International Financial Statistics (IFS) online database of the International Monetary Fund (IMF). Both IVs satisfy the exclusion condition because changes in such macro variables are arguably not directly related to firm-level decisions (e.g., innovation) through channels other than changes in the domestic competition landscape.[11]

Following the prior literature, we also make use of the large reductions in import tariffs as a natural experiment that represents exogenous shock in product market competition (Fresard 2010; Valta 2012; Li and Zhan 2019). Intuitively, a reduction in the import tariff reduces trade barriers and increases competition from abroad. A large reduction in import tariffs will significantly intensify the competition in a product market. Following Fresard (2010), Valta (2012), and Li and Zhan (2019), we created a dummy that indicates a negative shock in import tariffs if the tariff reduction is more than three times the median drop in the same 3-digit SIC industry over the entire sample period. As suggested by Li and Zhan (2019), we also excluded events when the tariff rate was less than 1%, since the impact of a further decrease in import tariffs for an already low-rate industry is likely to be minimal. The firms identified in each industry that experienced a negative shock were then matched to control firms, using propensity matching based on size, year, ROA, Tobin's Q, and change in R&D, and we compared their innovation activities.[12]

3.4. Sample Construction and Descriptive Statistics

We obtained the information of all US public firms from Compustat, and merged the data with the patent database of Kogan et al. (2017). Following the prior literature, we removed utility and financial firms (i.e., SIC codes that begin with 49 or 6), which are heavily regulated and involve very different innovation activities. We further merged the resulting sample with *Fluidity* data from the updated Hoberg–Philips Data Library, as in Hoberg et al. (2014), and with *Pctcomp* data from Feng Li's online database, as in Li et al. (2013). We arrived at a raw sample of 72,194 firm-year observations without missing control variables, comprising a span of 22 fiscal years (1997 to 2018).

Table 1 shows the summary statistics of the variables used in our study. For detailed definitions of the variables, see Appendix A Table A1. Interestingly, the median firm over our entire sample period has no explicit record of tangible innovation inputs or outputs. The average firm has a negative return on assets (ROA). The average total assets of the sample firms are about $276 million, and the average R&D expenditures account for about 7% of the total assets. The mean leverage ratio for firms is moderately high at about 51%. The average Tobin's Q of 2.35 reveals that the sample firms typically have higher market valuations relative to their intrinsic value. We present complete correlations between these variables in Appendix A Table A2. An initial review of the pairwise correlations table seems to suggest a positive correlation between competition measures and innovation. While *Fluidity* and *Pctcomp* are weakly related to traditional industry-level measures, they also seem to be correlated to each other, but not strongly (i.e., 15%). The methodological difference may account for this, with each measure capturing slightly different aspects of the actual competitive threats perceived by the managers (Li et al. 2013; Hoberg et al. 2014). Nonetheless, our results are robust for both measures.

Table 1. Summary Statistics.

Variables	N	Mean	SD.	0.25	Mdn	0.75
Main LHS Variables						
R&D_Intensity	72,194	0.07	0.15	0.00	0.00	0.08
Patent_F	47,337	0.51	1.06	0.00	0.00	0.69
Patent_I	50,317	0.57	1.10	0.00	0.00	0.69
Patent_Per_Emp	46,185	0.50	1.04	0.00	0.00	0.21
Patent_Cites(Filed)	50,318	0.79	1.67	0.00	0.00	0.00
Patent_Value(Filed)	50,318	0.76	1.67	0.00	0.00	0.24
Patent_Cites(Issued)	53,180	0.97	1.85	0.00	0.00	1.10
Patent_Value(Issued)	53,180	0.83	1.72	0.00	0.00	0.58
Main RHS Variable						
Fluidity	72,194	6.80	3.51	4.17	6.09	8.75
Pctcomp	26,240	0.57	0.47	0.23	0.42	0.76
Size	72,194	5.62	2.13	4.07	5.56	7.10
Ppe	72,194	0.25	0.23	0.07	0.17	0.35
Cashflow	72,194	−0.01	0.36	−0.02	0.07	0.12
Leverage	72,194	0.51	0.46	0.28	0.47	0.65
Roa	72,194	−0.11	0.58	−0.10	0.02	0.07
TobinsQ	72,194	2.35	3.19	1.14	1.58	2.51

This table reports the summary statistics of the main variables used in this study. The patent-related measures were obtained from Kogan et al. (2017), containing information on all patents granted by the US Patent and Trademark Office (USPTO). *Fluidity* and *Pctcomp* were developed by Hoberg et al. (2014) and Li et al. (2013), respectively. Other variables are constructed from the Compustat database. For a detailed definition of all variables, please refer to Appendix A Table A1.

4. Results and Discussion

4.1. Baseline Results on Competition and Innovation

We began by empirically testing the relation between innovation activities and the two new forward-looking competition measures. We first ran a baseline pooled OLS regression of innovation variables for *Fluidity* and *Pctcomp*. We included a vector of common variables that are thought to affect firms' innovation activities, as inspired by Aghion et al. (2005). We controlled for lagged size of firm, asset tangibility, book leverage, cash flow, Tobin's Q, and profitability. We also included 2-digit SIC industry- and year-fixed effects for all specifications to broadly account for differences in innovation opportunities across industries and over the years. All continuous variables are winsorized at the one-percent level at each tail of the distribution. The standard errors are all clustered at the firm level.

Table 2 reports our baseline results. All independent and control variables are lagged by one period. Columns (1) to (4) show the results for our main competition variable, *Fluidity*.[13] All specifications yielded a positive correlation with the number of patents filed or issued. The results are also consistent across the other two competition variables, patent filed per employee and R&D intensity. The results from Table 2 suggest that not only is competition positively associated with incentive to invest, but it is also correlated with the quantity of innovation output.[14] A one-standard-deviation change in *Fluidity* can lead to an approximately 5.5% increase in the number of patent applications or a 4% increase in R&D intensity in an average firm over the entire sample period.[15] The economic magnitude is significant considering the number of patents filed and the R&D intensity for an average firm. Larger firms seem to have higher numbers of patents filed and granted, whereas firms with a greater share of fixed assets seem on average to be associated with lower innovation, possibly due to the substitution effect between capital and innovation investment. The negative correlation between size and R&D intensity may be due to the effect of denominator scaling in the construction of the R&D intensity variable. Patenting activity relates negatively to profitability (i.e., *ROA*) but positively to market valuation (i.e., *TobinsQ*). There is also some evidence that higher innovation activity is associated with firms' lower cash flow; Brown et al. (2009) reiterated the importance of cash flow effects in R&D, especially for young firms. Furthermore, firms with higher leverage seem to be associated with lower levels of innovation activity. This observation coincides in part with the findings from Iqbal et al. (2022) that financial leverage diminishes innovative input and invention in Chinese public firms. Our baseline results using the firm-specific competition measures broadly support the argument that competition encourages innovation.

Table 2. Pooled OLS Regression: Fluidity and Innovation.

	(1) *Patent_F*	(2) *Patent_I*	(3) *Patent_Per_Emp*	(4) *R&D_Intensity*
Fluidity	0.0158 ***	0.0148 ***	0.0592 ***	0.0115 ***
	(0.004)	(0.004)	(0.003)	(0.000)
Size	0.2569 ***	0.2696 ***	0.0549 ***	−0.0079 ***
	(0.009)	(0.010)	(0.005)	(0.001)
Ppe	−0.2589 ***	−0.3504 ***	−0.3166 ***	−0.0523 ***
	(0.062)	(0.066)	(0.047)	(0.005)
Cashflow	0.0113	−0.0615 **	−0.0387	−0.1476 ***
	(0.026)	(0.024)	(0.037)	(0.006)
Leverage	−0.1454 ***	−0.1224 ***	−0.2656 ***	−0.0352 ***
	(0.016)	(0.016)	(0.021)	(0.003)
Roa	−0.1129 ***	−0.1138 ***	−0.0378 **	−0.0014
	(0.015)	(0.013)	(0.019)	(0.004)
TobinsQ	0.0322 ***	0.0181 ***	0.0359 ***	0.0020 ***
	(0.003)	(0.002)	(0.003)	(0.000)
Constant	−0.9032 ***	−0.8711 ***	−0.0750 **	0.0648 ***
	(0.046)	(0.048)	(0.036)	(0.004)
Industry FE.	Yes	Yes	Yes	Yes
Year FE.	Yes	Yes	Yes	Yes
Adj. R^2	0.36	0.36	0.26	0.48
Observations	47,337	50,317	46,185	72,194

This table reports the OLS regression results for the text-based firm-level competition measure *Fluidity*. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). Year and 2-digit SIC industry fixed effects are included in all specifications. Coefficients with ** and *** indicate significance level at 0.05 and 0.01 respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

Following Li and Zhan (2019), we also transformed our *Fluidity* variable into decile ranks numbered from 1 to 10, with 1 representing the lowest competitive threat and

10 the highest. Rank regressions are useful for making inferences about the order and magnitude of *Fluidity*. Rank regressions can reduce the concern that results may be driven by extreme values or skewed distribution of competition (Hribar et al. 2014; Chen and Gong 2019). The new variable (i.e., *Fluidity_rank*) is ranked based on the full sample as well as on each 2-digit SIC for each year. We repeated our baseline tests and report the results in Table 3.[16] The results are consistent with Table 2, demonstrating that *Fluidity_rank* yields unambiguous positive relations with different innovation measures regardless of sorting method. Inevitably, one might still have concerns that a subset of our sample could be driving these observations. It is plausible that such a positive relationship between competition and innovation exists only in the distribution extremes or for specific groups and that the relationship may not be as linear as we supposed.[17] In addition to the ranked regressions, to shed further light on this front we also constructed dummies to indicate whether a firm is in the top 30% (i.e., *HighFluidity*), the middle 40% (i.e., *MidFluidity*), or the bottom 30% (i.e., *LowFluidity*) in terms of *Fluidity* in the previous period. We then repeated the same regressions as in Table 2, using our new indicator dummies. The results are reported in Appendix A Table A4.

Table 3. Pooled OLS Regression: Fluidity (Rank) and Innovation.

	(1) *Patent_F*	(2) *Patent_F*	(3) *Patent_I*	(4) *Patent_I*	(5) *Patent_Per_Emp*	(6) *Patent_Per_Emp*	(7) *R&D_Intensity*	(8) *R&D_Intensity*
Fluidity_rank	0.0190 ***		0.0177 ***		0.0653 ***		0.0118 ***	
	(0.004)		(0.004)		(0.004)		(0.000)	
Fluidity_rank (SIC2 & Year)		0.0165 ***		0.0160 ***		0.0522 ***		0.0088 ***
		(0.003)		(0.003)		(0.003)		(0.000)
Size	0.2572 ***	0.2569 ***	0.2698 ***	0.2695 ***	0.0565 ***	0.0562 ***	−0.0076 ***	−0.0076 ***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.005)	(0.005)	(0.001)	(0.001)
Ppe	−0.2603 ***	−0.2626 ***	−0.3520 ***	−0.3532 ***	−0.3277 ***	−0.3409 ***	−0.0550 ***	−0.0571 ***
	(0.062)	(0.062)	(0.066)	(0.066)	(0.048)	(0.048)	(0.005)	(0.005)
Cashflow	0.0086	0.0071	−0.0641 ***	−0.0650 ***	−0.0545	−0.0646 *	−0.1522 ***	−0.1550 ***
	(0.026)	(0.026)	(0.024)	(0.024)	(0.037)	(0.038)	(0.006)	(0.006)
Leverage	−0.1453 ***	−0.1469 ***	−0.1222 ***	−0.1233 ***	−0.2698 ***	−0.2789 ***	−0.0366 ***	−0.0386 ***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.021)	(0.021)	(0.003)	(0.004)
Roa	−0.1126 ***	−0.1132 ***	−0.1134 ***	−0.1139 ***	−0.0387 **	−0.0427 **	−0.0017	−0.0028
	(0.015)	(0.015)	(0.013)	(0.013)	(0.019)	(0.019)	(0.004)	(0.004)
TobinsQ	0.0321 ***	0.0323 ***	0.0180 ***	0.0181 ***	0.0359 ***	0.0367 ***	0.0020 ***	0.0022 ***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.000)	(0.000)
Constant	−0.9018 ***	−0.8831 ***	−0.8698 ***	−0.8554 ***	−0.0396	0.0481	0.0770 ***	0.0950 ***
	(0.046)	(0.045)	(0.049)	(0.047)	(0.034)	(0.032)	(0.004)	(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.36	0.36	0.36	0.36	0.26	0.26	0.47	0.46
Observations	47,337	47,337	50,317	50,317	46,185	46,185	72,194	72,194

This table reports the OLS regression results for the decile rank of *Fluidity*, constructed using ranking of *Fluidity* (e.g., 1 = the decile with lowest competitive threat and 10 = the decile with the highest threats) from the full sample (i.e., columns (1), (3), (5), and (7)) and from each 2-digit SIC of a specific year (i.e., columns (2), (4), (6), and (8)). All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in the parentheses (Cameron and Trivedi 2010). Year and 2-digit SIC industry fixed effects are included in all specifications. Coefficients with *, **, or *** indicate significance levels of 0.10, 0.05, and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

The bottom line is that the observed results are generally consistent and do not seem to differ greatly according to how we sort *Fluidity*. An average firm facing high levels of competitive threat seems to file more patents, and the opposite is true for firms experiencing low competitive threat. On average, firms that encounter a moderate level of competition do not seem to exhibit any statistically significant relation with patent counts compared with the other two groups. In the next section of this paper, we therefore focus on reduced-form linear regressions with IVs for competition measures, as in Xu (2012) and Li and Zhan (2019).

4.2. Evidence from Import Tariff

4.2.1. Instrumental Variables

To address the potential concerns about endogeneity between competition and innovation, we implemented instrumental variables through two-stage least-squares regressions.

Following Xu (2012), we used import tariffs and foreign exchange rates as the IVs for our main competition variable, *Fluidity*.[18] As discussed above, this satisfies the relevance condition because these rates highly correlate with our competition measures and are arguably not directly related to firm-level innovation through channels other than competition.

Table 4 reports the results for our first-stage and second-stage IV estimates. As shown in the first-stage regressions (i.e., columns (5) to (8)), we regressed *Fluidity* on import tariffs, foreign exchange rates, firm-level controls, and year- and industry-fixed effects. The consistently negative indicators for *Import Tariff* show that higher import tariffs reduce competition. Intuitively, an increase in the tariff reduces the price competitiveness of foreign firms. The positive coefficients for *Exchange Rate* imply that a higher valuation of the US dollar encourages imports, because it reduces the prices of foreign goods.[19] We then applied the predicted values of *Fluidity* from our first-stage IV regressions in the second stage. To examine the relevance condition for our instruments, we used F testing to examine whether they were jointly equal to zero. All F statistics appeared statistically significant in our first-stage regressions, implying that the instruments did indeed relate to our competition measures and that the relevance condition is thus satisfied. To assess the validity of our instruments, we conducted formal Hansen J-statistics testing for the overidentifying restrictions and the null that the instruments are valid. The J statistics were not found to be statistically significant, with a p-value far above the 10% threshold, indicating that the instruments are uncorrelated with the error terms of the model, and therefore satisfying the exclusion condition. We also performed the Anderson–Rubin (AR) X^2 test, which is robust to weak instruments, to examine the significance of our potentially endogenous competition measures. Significant X^2 statistics were observed for all our dependent variables, indicating that the coefficients of *Fluidity* indeed significantly differed from zero and the estimates from the second stage regressions are robust to weak instruments. Columns (1) to (4) report the second stage IV regression estimates for various innovation measures. In our second-stage estimations, we observed unambiguous positive coefficients for *Fluidity* across various measures of innovation, and our results support a causal inference that competition increases firms' innovation.

Table 4. Two-Stage Least-Squares Regression: *Fluidity*.

	Second-Stage Estimation				**First-Stage Estimation**			
	(1) ***Patent_F***	**(2)** ***Patent_I***	**(3)** ***Patent_Per_Emp***	**(4)** ***R&D_Intensity***	**(5)** ***Patent_F***	**(6)** ***Patent_I***	**(7)** ***Patent_Per_Emp***	**(8)** ***R&D_Intensity***
Fluidity	0.1506 ***	0.1370 ***	0.1773 ***	0.0292 ***				
	(0.028)	(0.028)	(0.020)	(0.002)				
Import Tariff (IV)					−0.3617 ***	−0.3788 ***	−0.3630 ***	−0.4081 ***
					(0.052)	(0.053)	(0.054)	(0.050)
Exchange Rate (IV)					0.1199 ***	0.1127 ***	0.1264 ***	0.0572 *
					(0.034)	(0.034)	(0.035)	(0.031)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen's J-statistic	0.05	0.29	0.54	0.36				
(p-value)	(0.83)	(0.59)	(0.46)	(0.5)				
AR X^2-statistic (p-value)	44.4 (<0.01)	34.9 (<0.01)	66.2 (<0.01)	90.0 (<0.01)				
F-statistic (p-value)					27.3 (<0.01)	27.5 (<0.01)	25.9 (<0.01)	33.8 (<0.01)
Adj R^2	0.250	0.279	0.056	0.296	0.427	0.428	0.429	0.461
Observations	24,938	26,601	24,451	38,993	24,938	26,601	24,451	38,993

This table presents the 2SLS results for our main competition measure, *Fluidity*. Columns (1) to (4) report the second-stage estimations, and columns (5) to (8) show the results of the first-stage regressions. The included IVs for *Fluidity* are the import tariffs (available for firms in the manufacturing industry) and the trade-weighted foreign exchange rates. The included control firms are identical to those in Table 2. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). Year- and 2-digit SIC industry-fixed effects are included in all specifications. Full table with coefficients for controls is available upon request to the authors. Coefficients with * and *** indicate significance levels of 0.10 and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

4.2.2. Exogenous Shock in Tariff

We further observed causal evidence linking product market competition and innovation by identifying exogenous decreases in the import tariffs. The US import data report numerous large industry-specific decreases in tariffs between 1990 to 2008.[20] Following Fresard (2010), Valta (2012), and Li and Zhan (2019), we define an exogenous negative shock to occur in each industry year when the import charge reduction is more than three times the median drop in the same industry over our sample period. As suggested by Li and Zhan (2019), we excluded events when the tariff rate was less than 1%, since the impact of a further decrease in import tariff for an already low-rate industry is likely to be minimal. We found a total of 91 exogenous tariff shocks during the sample period and identified 1625 firm-year observations of exogenous reductions in import charges. Using propensity score matching with replacement, we paired firms that experienced a negative tariff decrease in a specific year with firms from the same year matched for firm size, ROA, Tobin's Q, and change in R&D intensity. A benefit of matching is that it makes no explicit assumption on functional forms, in contrast with conventional OLS regression. Table 5 reports the changes in patents granted for the treated and control firms before and after the tariff-reduction event.[21] Notably, the treated firms appear to exhibit a higher level of patenting activities around the event compared with the controls. However, the difference between the two groups increased during and after the event year, with statistical significance.[22] Intuitively, firms that anticipate and experience higher competition from imports are more likely to engage in patenting activities in future.[23] This result is consistent with our previous results demonstrating that competition stimulates innovation in terms of patents issued.

Table 5. Exogenous Negative Shock on Import Tariff.

Matched on: Lagged *Size, ROA, Year, TobinsQ, and Δ in R&D Intensity*	***Log(1 + Δ Patent Issued)***		
	(1)	**(2)**	**(3)**
	t* − *1	***t (Event Year)***	***t + 1***
Treated	0.4397	0.4693	0.4305
Matched	0.4143	0.3928	0.3541
Difference	0.0254	0.0765 **	0.0764 **
T-stat	0.79	2.33	2.30
(*p*-value)	(0.4291)	(0.0199)	(0.0217)

We define an exogenous negative shock to occur in each industry year when the import charge reduction is more than three times the median drop in the same industry over the sample period between 1990 to 2008. We identified a total of 91 exogenous tariff reductions and 1625 firm-year observations that indicated such a shock. We then use propensity score matching with replacement to match each treated firm with a control firm of similar characteristics. Coefficients with ** indicate significance level of 0.05. For detailed definitions of variables, please refer to Appendix A Table A1.

4.3. Quality of Innovation

This paper has so far discussed the quantitative indicators of innovation under heightened competition. It is also important to shed some light on the qualitative aspects of innovation output. We used patent citations and patent value as the two proxies for innovation quality, as in Kogan et al. (2017). We repeated our baseline regression by substituting the dependent variables with the two quality measures for patents filed and issued. Results are presented in Table 6. It is reassuring to observe consistent and statistically significant relations between *Fluidity* and both measures of innovation quality. Our results unambiguously suggest that firms under competition produce better quality patents in terms of patent citations and patent value. The presence of greater competition leads to not only higher patenting activities but also higher quality.

Table 6. Competition and Innovation Quality.

	(1) *Patent_Cites(Filed)*	(2) *Patent_Value(Filed)*	(3) *Patent_Cites(Issued)*	(4) *Patent_Value(Issued)*
Fluidity	0.0296 ***	0.0199 ***	0.0352 ***	0.0151 ***
	(0.005)	(0.006)	(0.006)	(0.006)
Size	0.3427 ***	0.4643 ***	0.3911 ***	0.4916 ***
	(0.012)	(0.014)	(0.014)	(0.015)
Ppe	−0.3645 ***	−0.4674 ***	−0.5443 ***	−0.6157 ***
	(0.088)	(0.096)	(0.102)	(0.100)
Cashflow	−0.0068	0.0581	−0.1167 **	−0.0274
	(0.041)	(0.041)	(0.045)	(0.040)
Leverage	−0.2812 ***	−0.2060 ***	−0.2527 ***	−0.1750 ***
	(0.025)	(0.025)	(0.027)	(0.025)
Roa	−0.1465 ***	−0.2082 ***	−0.1738 ***	−0.2025 ***
	(0.023)	(0.023)	(0.025)	(0.023)
TobinsQ	0.0591 ***	0.0606 ***	0.0386 ***	0.0480 ***
	(0.005)	(0.005)	(0.004)	(0.004)
Constant	−1.1617 ***	−1.7895 ***	−1.2147 ***	−1.8014 ***
	(0.063)	(0.073)	(0.071)	(0.074)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.32	0.38	0.31	0.39
Observations	50,318	50,318	53,180	53,180

This table reports the results for the regressions of patent citations and patent values on our main competition measure, *Fluidity*. Columns (1) and (2) report the results for patents filed, and columns (3) and (4) report those for patents issued. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). Year- and 2-digit SIC industry-fixed effects are included in all specifications. Coefficients with ** and *** indicate significance levels of 0.05 and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

5. Conclusions

Gilbert (2006) reiterates that the inconclusiveness of the theory regarding the impact of competition on innovation is due to varying model assumptions. Prior empirical research was often bound by the limitations of traditional industry-level measures. This paper attempts to shed light on the long-debated relationship by taking a unique managerial perspective at the firm level. By utilizing the two text-based competition measures derived from firms' 10-K filings, we were able to capture substantial within-industry variation to reassess this relation. Arguably, the managers who drafted 10-K filings are a more appropriate resource to gauge the true competitive pressure faced by their firms than any industry indicator or concentration ratios calculated from historical sales figures. We found that product market threats unambiguously encourage firms towards greater innovation, in terms of both quantity and quality. Most importantly, we also provide causal inference by addressing the endogeneity issues associated with competition and innovation, making use of instrumental variables and exogenous shocks in import tariffs. Finally, we hope to offer some insights and practical considerations for policymakers concerning trade policies, anti-trust regulations, and innovation. For instance, regulators could leverage novel text-based competition measures to gauge firms' perceived competitive threats and utilize this information as a strategic instrument to monitor foreign trade risks and foster domestic innovation. In parallel, firms could also scrutinize perceived competitive threats from their rivals, and develop appropriate strategies to escape competition through innovation.

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Appendix A

Table A1. Variable Definitions.

Main LHS Variables	
Patent_F	Natural log of one plus the number of patents filed in year *t*
Patent_I	Natural log of one plus the number of patents issued in year *t*
Patent_Per_Emp	Natural log of one plus the number of patents filed in year *t* divided by the total number of employees in year *t*
R&D_Intensity	R&D expenditures divided by the total assets
Patent_Cites(Filed)	Natural log of one plus total citation received from all patents filed in year *t*
Patent_Value(Filed)	Natural log of one plus total patent values received from all patents filed in year *t*
Patent_Cites(Issued)	Natural log of one plus total citation received from all patents issued in year *t*
Patent_Value(Issued)	Natural log of one plus total patent values received from all patents issued in year *t*
Main RHS Variable	
Fluidity	A measure for competitive threat, as in Hoberg et al. (2014)
Pctcomp	A measure for competitive threat, as in Li et al. (2013)
Controls	
Size	Natural log of total assets
Cashflow	Cash flow from operating activities minus capital expenditure and normalized by total assets
Ppe	Total property, plant, and equipment divided by total assets
Leverage	Total debt divided by the total assets
Roa	Net income divided by the total assets
TobinsQ	Book value of assets plus market value of equity minus book value of equity and normalized by total assets

Table A2. Pairwise Correlation.

	Variables Names	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
(1)	*R&D_Intensity*	1.00															
(2)	*Patent_F*	0.11	1.00														
(3)	*Patent_I*	0.14	0.85	1.00													
(4)	*Patent_Per_Emp*	0.32	0.70	0.54	1.00												
(5)	*Fluidity*	0.41	0.08	0.08	0.25	1.00											
(6)	*Pctcomp*	0.22	0.03	−0.03	0.16	0.15	1.00										
(7)	*Size*	−0.34	0.33	0.35	−0.04	−0.08	−0.27	1.00									
(8)	*Ppe*	−0.27	−0.09	−0.11	−0.18	−0.04	−0.11	0.21	1.00								
(9)	*Cashflow*	−0.51	0.06	0.05	−0.10	−0.25	−0.09	0.41	0.15	1.00							
(10)	*Leverage*	−0.01	−0.05	−0.05	−0.13	−0.02	−0.17	0.06	0.12	−0.34	1.00						
(11)	*Roa*	−0.40	0.06	0.05	−0.05	−0.21	−0.03	0.36	0.08	0.83	−0.44	1.00					
(12)	*TobinsQ*	0.26	0.08	0.04	0.17	0.17	0.12	−0.18	−0.13	−0.36	0.23	−0.35	1.00				
(13)	*Patent_Cites(Filed)*	0.12	0.84	0.74	0.61	0.08	0.12	0.24	−0.09	0.04	−0.07	0.04	0.10	1.00			
(14)	*Patent_Value(Filed)*	0.07	0.86	0.83	0.48	0.07	−0.00	0.41	−0.07	0.08	−0.04	0.07	0.09	0.85	1.00		
(15)	*Patent_Cites(Issued)*	0.16	0.77	0.82	0.54	0.09	0.04	0.26	−0.12	0.02	−0.06	0.03	0.07	0.77	0.77	1.00	
(16)	*Patent_Value(Issued)*	0.08	0.78	0.87	0.42	0.06	−0.06	0.43	−0.09	0.08	−0.02	0.07	0.06	0.69	0.85	0.86	1.00

For detailed definitions of variables, please refer to Appendix A Table A1.

Table A3. Alternative Pooled OLS Regression: Industry- and Year-Fixed Effects.

	(1) *Patent_F*	(2) *Patent_I*	(3) *Patent_Per_Emp*	(4) *R&D_Intensity*
Fluidity	0.0184 ***	0.0176 ***	0.0654 ***	0.0120 ***
	(0.004)	(0.004)	(0.003)	(0.000)
Size	0.2579 ***	0.2710 ***	0.0542 ***	−0.0079 ***
	(0.009)	(0.010)	(0.005)	(0.001)
Ppe	−0.2607 ***	−0.3358 ***	−0.3223 ***	−0.0511 ***
	(0.063)	(0.067)	(0.048)	(0.005)
Cashflow	0.0093	−0.0633 **	−0.0422	−0.1473 ***
	(0.026)	(0.025)	(0.038)	(0.006)
Leverage	−0.1457 ***	−0.1257 ***	−0.2585 ***	−0.0354 ***
	(0.016)	(0.016)	(0.021)	(0.003)
Roa	−0.1137 ***	−0.1147 ***	−0.0384 **	−0.0019
	(0.015)	(0.013)	(0.019)	(0.004)
TobinsQ	0.0326 ***	0.0196 ***	0.0350 ***	0.0020 ***
	(0.003)	(0.002)	(0.003)	(0.000)
Constant	−0.9257 ***	−0.9029 ***	−0.1135 ***	0.0610 ***
	(0.047)	(0.049)	(0.036)	(0.004)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.36	0.36	0.28	0.48
Observations	47,297	50,275	46,136	72,120

This table reports the alternative OLS regression results for our main text-based firm-level competition measure, *Fluidity*, including an additional set of *industry* x *year* dummies. All independent variables are lagged by one period. Standard errors are clustered to account for potential serial correlation and are reported in the parentheses (Cameron and Trivedi 2010). Coefficients with ** and *** indicate a significance level of 0.05 and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

Table A4. High, Mid, and Low Competitive Threats and Patent Filed.

	(1) *Patent_F*	(2) *Patent_F*	(3) *Patent_F*	(4) *Patent_F*	(5) *Patent_F*	(6) *Patent_F*
HighFluidity	0.0755 ***					
	(0.022)					
HighFluidity(SIC2)		0.0795 ***				
		(0.018)				
MidFluidity			−0.0002			
			(0.015)			
MidFluidity(SIC2)				−0.0060		
				(0.015)		
LowFluidity					−0.0746 ***	
					(0.021)	
LowFluidity(SIC2)						−0.0705 ***
						(0.019)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.35	0.35	0.35	0.35	0.35	0.35
Observations	47,337	47,337	47,337	47,337	47,337	47,337

This table reports the OLS regression results for dummies indicating whether a firm is in the top 30%, middle 40%, or bottom 30% in terms of competitive threats (i.e., *Fluidity*). The three dummies in columns (1), (3), and (5) are sorted based on the full sample, and columns (2), (4), and (6) are sorted within each 2-digit SIC industry. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). Year and 2-digit SIC industry fixed effects are in all specifications. Full table with coefficients for controls is available upon request to the authors. Coefficients with *** indicate a significance level 0.01. For detailed definitions of variables, please refer to Appendix A Table A1.

Table A5. Pooled OLS Regression: *Pctcomp* and Innovation.

	(1) *Patent_F*	(2) *Patent_I*	(3) *Patent_Per_Emp*	(4) *R&D_Intensity*
Pctcomp	0.0854 ***	0.0490 **	0.1481 ***	0.0170 ***
	(0.024)	(0.025)	(0.025)	(0.001)
Size	0.3177 ***	0.3352 ***	0.0737 ***	−0.0008 *
	(0.013)	(0.013)	(0.007)	(0.000)
Ppe	−0.2395 **	−0.3263 ***	−0.1694 ***	−0.0290 ***
	(0.096)	(0.102)	(0.064)	(0.004)
Cashflow	0.1718 *	−0.0077	−0.3720 ***	−0.0537 ***
	(0.088)	(0.091)	(0.096)	(0.008)
Leverage	−0.3035 ***	−0.2990 ***	−0.5191 ***	−0.0356 ***
	(0.055)	(0.058)	(0.045)	(0.003)
Roa	−0.3938 ***	−0.4338 ***	−0.3969 ***	−0.0499 ***
	(0.050)	(0.052)	(0.054)	(0.006)
TobinsQ	0.0857 ***	0.0581 ***	0.0820 ***	0.0048 ***
	(0.012)	(0.012)	(0.012)	(0.001)
Constant	−1.2645 ***	−1.2121 ***	0.0899 *	0.0503 ***
	(0.075)	(0.078)	(0.051)	(0.004)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.39	0.40	0.26	0.34
Observations	24,799	26,240	24,373	26,240

This table reports the OLS regression results for our alternative text-based firm-level competition measure, *Pctcomp*. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). Year- and 2-digit SIC industry-fixed effects are included in all specifications. Coefficients with *, **, or *** indicate significance levels of 0.10, 0.05, and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

Table A6. Two-Stage Least-Squares Regression–*Pctcomp*.

	Second-Stage Estimation				First-Stage Estimation			
	(1) *Patent_F*	(2) *Patent_I*	(3) *Patent_Per_Emp*	(4) *R&D_Intensity*	(5) *Patent_F*	(6) *Patent_I*	(7) *Patent_Per_Emp*	(8) *R&D_Intensity*
Pctcomp	3.7059 ***	3.5835 ***	2.3808 ***	0.2443 ***				
	(1.200)	(1.214)	(0.824)	(0.055)				
Import Tariff (IV)					−0.0109 ***	−0.0114 ***	−0.0103 ***	−0.0114 ***
					(0.003)	(0.003)	(0.003)	(0.003)
Exchange Rate (IV)					0.0118 **	0.0108 *	0.0111 *	0.0108 *
					(0.006)	(0.006)	(0.006)	(0.006)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen's *J*-statistic	1.02	0.56	0.77	4.36				
(*p*-value)	(0.31)	(0.46)	(0.38)	(0.04)				
AR X^2-statistic	25.22	19.27	17.90	32.16				
(*p*-value)	(<0.01)	(<0.01)	(<0.01)	(<0.01)				
F-statistic					8.50	9.04	7.55	9.04
(*p*-value)					(<0.01)	(<0.01)	(<0.01)	(<0.01)
Adj R^2	−0.91	−0.71	−0.70	−1.99	0.33	0.34	0.33	0.34
Observations	13,388	14,179	13,236	14,179	13,388	14,179	13,236	14,179

This table presents the 2SLS results for our alternative competition measure, *Pctcomp*. Columns (1) to (4) report the second-stage estimations, and columns (5) to (8) show the results for the first-stage regressions. Note that the R^2 from IV estimation can be negative because *SSR* for IV can be larger than *SST*, which should not be directly interpreted (Wooldridge 2015). The included IVs for *Pctcomp* are the import tariffs (available for firms in the manufacturing industry) and the trade-weighted foreign exchange rates. Note that column (4) shows a significant *J* statistic, but it was confirmed in a separate test that the second stage IV estimate remains significant and consistent when we remove *Exchange Rate* from the first stage. All independent variables are lagged by one period. Standard errors are clustered by firms to account for potential serial correlation and are reported in parentheses (Cameron and Trivedi 2010). The included control firms are identical to those in Table 2. Year- and 2-digit SIC industry-fixed effects are included in all specifications. Full table with coefficients for controls is available upon request to the authors. Coefficients with *, **, or *** indicate a significance level of 0.10, 0.05, and 0.01, respectively. For detailed definitions of variables, please refer to Appendix A Table A1.

Notes

1 See Kamien and Schwartz (1975) and Gilbert (2006) for a comprehensive literature review on the topic.

2 A large drop in import tariff is often used to represent exogenous shock to domestic firms' competitive environment in the finance and accounting literature (Fresard 2010; Valta 2012; Li and Zhan 2019; Lee and Wen 2020)

3 See Kamien and Schwartz (1975) and Gilbert (2006) for comprehensive surveys about the theories and empirical evidence of the relation between market competition and innovation.

4 Interestingly, their study utilized experimental economics techniques to study the impact of competition on innovation, and the laboratory setting provided exogenous control over key variables. In brief, they conducted two experiments where pairs of subjects were matched for a number of periods. In each period, one of the two subjects can choose an R&D investment that determines the probability of a successful innovation with a quadratic cost function. Rents are distributed to each subject based on their relative technological location in their sector. If subjects are in an unleveled sector, the leader receives a positive monopoly rent, while the laggard earns nothing.

5 Traditional industry classification (e.g., SIC or NAICS) may not be a perfect indication of direct competition among firms. Firms today can compete across numerous different industries and even overseas. The construction of *Fluidity* is based on the similarity of a firm's product description with all other firms, in order to define new industry classifications. *Pctcomp* is constructed directly from each firm's 10K filings, where managers report their perceptions of the level of competition. See Hoberg et al. (2014) and Li et al. (2013) for more details.

6 While both measures capture competition threats in a forward-looking manner through firms' qualitative disclosure, we believe that the construction of *Fluidity* from product descriptions resembles more closely the definition of product market competition. Moreover, the number of observations for *Fluidity* (*N* = 72,194) was substantially larger than that for *Pctcomp* (*N* = 26,240). Nonetheless, we repeated our main regressions with *Pctcomp* and achieved very similar results which are shown in our Appendix A tables.

7 The data for *Pctcomp* were published on Feng Li's website (http://webuser.bus.umich.edu/feng/, accessed on 20 February 2020).

8 A recent working paper by Pancost and Schaller (2022) argues that not only can the instrumental approach be applied to address omitted variables or simultaneity, but it also alleviates attenuation bias from classical errors in variables.

9 The trade data can be obtained from Schott's International Economics Resource Page Trade Data and Concordances at https://faculty.som.yale.edu/peterschott/international-trade-data/, accessed on 9 March 2020.

10 Our results remain consistent if we convert to real exchange using CPI data from IMF statistics benchmarked to year 2010.

11 While most of the recent trade agreements are negotiated at a higher political and economic level between countries and within international institutions (e.g., World Trade Organization), we argue that decisions to change tariffs are not directly correlated with domestic firms' innovation other than through the channel of product market competition.

12 Note that the negative shock is industry-specific; therefore, all control firms are from other untreated industries with similar matching characteristics.

13 We observed highly similar results using our alternative competition measure, *Pctcomp.* Please refer to Appendix A Table A5.

14 It is also reassuring to see that our results were even more robust when we included an additional *Industry* x *Year* fixed effect (see Appendix A Table A3). This is equivalent to controlling for traditional measures such as *HHI* or *CR* that vary only at industry and year levels. This implies that the within-firm variations of competitive threats explain the variation of innovative activity substantially better than traditional measures such as *HHI* or *CR*.

15 Note that this interpretation is approximately true only when the number of patents filed is much greater than one, due to the "log(1 + y)" transformation.

16 Not shown in the paper. We also observed almost identical results when similar regressions were performed on ranked *Pctcomp*.

17 Considering that several prior studies have documented potential non-linear relationships between competition and innovation, we also ran regressions with quadratic terms in separate tests. However, in most setups the square terms are generally not statistically significant nor consistent with our main competition measure.

18 We also obtained very similar results using *Pctcomp*, as shown in Appendix A Table A6.

19 An increase in foreign exchange rate (foreign/USD) will increase *Fluidity* (i.e., competition) because imports are cheaper, and vice-versa.

20 The sub-sample period is essentially the overlap of the patent and the import data.

21 Notably, this matching exercise did not yield such robust results when Δ in Patent Filed and Δ in R&D intensity were used instead. Potentially, a fundamental caveat in this setup is that PSM could not account for unobserved heterogeneity between the treated and the matched groups, and that the closest controls had to be from different industries due to the entire industry experiencing a tariff shock. Alternatively, application to accelerate pending patents from the USPTO might be more feasible for firms anticipating imminent competition, compared with immediate increases in R&D expenditures or in immature patent filings.

22 The statistically insignificant difference *T* statistics in column (1) is consistent with the parallel trend assumption in matching.

[23] Upon anticipation of imminent competition, firms could potentially engage in numerous ways to speed up their pending patent applications through the Track One Program, a Patent Prosecution Highway (PPH) request, petitioning to accelerate examination, or the After Final Consideration Pilot (AFCP) form, etc.

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