Technological Peer Pressure and Product Disclosure

Sean Cao
J. Mack Robinson College of Business
Georgia State University
(404) 413-7206 (office)
scao@gsu.edu

Guang Ma
NUS Business School
National University of Singapore
(+65) 6601-2838 (office)
bizmag@nus.edu.sg

Jennifer Wu Tucker
Fisher School of Accounting
University of Florida
(352) 273-0214 (office)
jenny.tucker@warrington.ufl.edu

Chi Wan
School of Management
University of Massachusetts Boston
(617) 287-7683 (office)
chi.wan@umb.edu

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ABSTRACT

The relation between product-market competition and voluntary corporate disclosure is fundamental, but empirical evidence of this relation has been mixed. One reason for the mixed evidence could be that both competition and disclosure are multidimensional. In this study we introduce a firm-specific measure of the technological aspect of competition—technological peer pressure—to the accounting literature and examine an overlooked type of voluntary disclosure—firm-initiated product-development-related press releases ("product disclosure"). We argue that empirical examinations of the theorized negative relation between competition and disclosure require the type of voluntary disclosure to be relevant to the dimension of competition under examination to ensure that firms incur significant proprietary costs of disclosure. We expect a negative relation between technological peer pressure and product disclosure because the latter reveals firms' strategies, allocations, and progress of technological investments in product development to competitors. In contrast, we do not expect a negative relation between technological peer pressure and management earnings forecasts—the most common type of voluntary disclosure used in accounting research—because earnings projections reveal little about technological investments. Our test results are consistent with these expectations. Our study highlights the importance of understanding the multidimensionality of product-market competition and voluntary disclosure.

Keywords: Competition, proprietary costs, voluntary disclosure, technology

Data availability: All data are available from public sources.

I. INTRODUCTION

The relation between competition in the product market and voluntary corporate disclosure to the capital market is fundamental. In a pure exchange economy, corporate disclosure only affects the redistribution of wealth, but disclosure has real effects in an economy with production (Dye 2001). The relation between product-market competition and capital-market disclosure has drawn considerable interest from researchers in economics, finance, and accounting. Theorists have built models to uncover the relation between competition and disclosure in various situations and generally predict a negative relation between the two constructs (Jovanovic 1982; Verrecchia 1983; Wagenhofer 1990; Gigler 1994; Hayes and Lundholm 1996). Empirical evidence of this relation has been mixed (Beyer, Cohen, Lys, and Walther 2010, 306). One reason for the mixed evidence could be that competition and disclosure are both multidimensional.

The economics literature has adopted a definition of product market that encompasses all revenue-generating activities, including research and development (R&D), production, distribution, sales of products, and services (Severinov 2001; Asker and Ljungqvist 2010; Gersbach and Schmutzler 2012). That is, the literature defines product market broadly to include upstream R&D activity and downstream price setting. Firms may compete to invest in technology to develop or improve products, obtain reliable suppliers and low prices for materials, hire skilled workers, improve production efficiency, secure distribution channels, price finished products, and advertise to or retain customers. Thus, competition in the product market is multifaceted and a firm may face different rivals on each front.

Meanwhile, in the capital market firms may voluntarily disclose various types of information. For example, firms may provide information about their contracts with suppliers; restrictions on departing employees; research and product developments; production plans; store openings and closings; alliances; pricing strategies; key customers; and management earnings forecasts (MEF). Thus, voluntary disclosure is also multidimensional.

In this study we call researchers' attention to the multidimensionality of competition and disclosure by (1) introducing a measure of technological competition and comparing the measure with other firm-specific measures of competition and (2) examining company-initiated product-development-related voluntary disclosure (hereafter, "product disclosure") and contrasting it with MEF—the most common type of voluntary disclosure in accounting research. One implication of the multidimensionality of competition and disclosure is that researchers cannot simply pair a measure of competition with a measure of disclosure and expect a negative relation between the two. For a given dimension of competition, some types of disclosure are relevant to competitors and therefore could impose proprietary costs on the disclosing firm (we refer to this property as "alignment"), whereas other types are not relevant.[1] For example, if one is interested in competition for skilled employees, then disclosure about union negotiations and fringe benefits is more relevant than disclosure about distribution channels. We examine the association between competition and disclosure using alternative measures of competition and disclosure and only expect a significantly negative association when alignment exists.

We focus on technological competition for two reasons. First, in theory, technological innovation is the most important force driving economic growth in the long run (Solow 1956, 1957). Second, in practice, technology has long been the driver of economic growth as the US economy transitions from an industrial economy to a knowledge-based economy (Galor and Weil 2000; Zingales 2000; Koten 2013).[2] The ability of firms to innovate and use technology to

[1] We view "relevance" in relative terms. Because a firm is a nexus of various explicit or implicit contracts, it is difficult to argue that a piece of information about a firm has absolutely no relevance to certain aspects of the firm.
[2] The global market for products manufactured by research-intensive industries has grown more than twice as quickly as that for other manufactured goods (National Science Foundation 1998).

maintain competitiveness is vital to their success and even survival (Vives 1989; Grove 1996; Eisdorfer and Hsu 2011). By "technological competition," we mean the extent to which a firm invests in technology that will be used to develop or improve its products.[3] So far, there is scant evidence on the effects of technological competition on corporate disclosure.

We call our measure of technological competition "technological peer pressure" (*TPP*), which we develop from the technology-based product-market rivalry variable introduced by Bloom, Schankerman, and Van Reenen (2013). We operationalize "technology" by using a firm's cumulative R&D investments in recent years (hereafter, "R&D stock"). We identify "peers" by evaluating the closeness of two firms in the product-market space spanned by 4-digit SIC industries, where a firm's location is determined by its segment sales distribution in these industries. We calculate "pressure" as the pool of peers' R&D stock relative to the firm's own R&D stock, using the closeness of peer firms to the sample firm as the weight in aggregating peers' R&D stock.[4] *TPP* measures the aggregate technological advances of firms that compete with the sample firm in the product market relative to the sample firm's own technological preparedness. A higher value of *TPP* indicates that the firm faces more intense technological competition.

We compare *TPP* with other firm-specific measures of competition in the literature. One measure is introduced by Li, Lundholm, and Minnis (2013), who divide the number of competition-related words in a firm's 10-K report by the total number of words in the report. We refer to their measure as *LLMComp*. The other measure is introduced by Hoberg, Phillips, and

[3] Firms may use technology to develop new products and services, enhance production efficiency, facilitate communication inside the company, etc. Our approach emphasizes the use of technology in developing and improving products and services.

[4] One data problem from using R&D information is that some firms may engage in R&D activity but report no R&D expenses (Koh and Reeb 2015). These firms tend to be small and might conduct R&D through their joint ventures. One way to overcome this problem is to use patent data instead of R&D data, but this alternative has its own problem: firms often avoid patent filings to prevent information leakage to competitors. For example, the majority of European firms do not file patents for their technological breakthroughs (Koh and Reeb).

Prabhala (2014), who measure the extent to which words used by a firm in its business descriptions of the 10-K report are adopted or dropped by its peers. The authors refer to this measure as *Fluidity*. Our *TPP* measure is positively correlated with these alternative measures, but the correlations are low, suggesting that *TPP*, *LLMComp*, and *Fluidity* capture different aspects of competition.

We examine product disclosure for two reasons. First, if one is interested in technological competition, then product disclosure is the most relevant type of voluntary disclosure. Product disclosure reveals where the firm invests in technology for product development and improvement, as well as how these investments have progressed, to both the firm's investors and rivals. Firms can incur significant proprietary costs if their competitors take actions, based on such disclosure, detrimental to the disclosing firm. Second, firms frequently make product disclosure and constantly monitor their rivals' product disclosure to use the gleaned information in their own strategic planning (Chartered Institute of Marketing 2009, 5; Sharp 2009, 165-198; Helm 2011). With the exceptions of Ma (2012) and Merkley (2014), however, prior research has not examined product disclosure in large samples. Ma finds that investor reactions to operations-related disclosure, which includes product disclosure, are larger in magnitude than their reactions to 10-K/Q reports and 8-K filings. He does not separately examine product disclosure, though. Merkley collects narrative R&D disclosure in 10-K reports, but that disclosure is not as timely as the product disclosure that we collect.

We obtain firm-initiated press releases related to R&D stage, product introduction, improvement, or retirement. We observe significantly positive return reactions to product-disclosure releases, suggesting that investors welcome product disclosure. Furthermore, these reactions increase significantly with the total number of words contained in a release, suggesting that a word count can proxy for the amount of information contained in the release. So, for each firm-year we measure product disclosure as the total number of words in product-disclosure press releases issued by the firm during the fiscal year. To understand the extent to which proprietary information is contained in a product-disclosure press release, we interviewed three experts in the computer/technology industries and surveyed 206 participants who passed the financial literacy and computer/technology knowledge screening on Amazon Mechanical Turk. Their responses indicate that product disclosure has proprietary content.

We compare our product-disclosure measure with MEF and Merkley's (2014) measure of R&D disclosure. We find a significantly positive correlation between our measure and Merkley's and a significantly positive but much smaller correlation between our measure and the frequency of MEF issued during the same firm-year. These comparisons have three implications. First, the positive correlations suggest that a firm providing one type of disclosure is more likely to provide other types of disclosure perhaps due to management's overall attitude toward transparency. Second, the fact that our measure correlates more highly with Merkley's than with MEF suggests that our measure captures a construct closer to Merkley's than to MEF. Last, the low correlation between our measure and MEF implies that managers treat product disclosure and MEF as distinct types of disclosure, each with its own purpose.

We use alternative measures of competition and disclosure to test the theorized negative relation between competition and disclosure for the sample period of 2003–2012. First, we use a firm-year's product disclosure as the dependent variable and examine the associations of *TPP*, *LLMComp*, and *Fluidity,* all measured at the end of the previous year, with product disclosure of the current year. We find that *TPP* has a significantly negative and strong economic association with product disclosure: a firm that moves from the lowest decile of *TPP* to the highest decile reduces its product disclosure by 44.7%. We find that *LLMComp* is not associated with product disclosure and *Fluidity* is significantly positively associated with product disclosure. *TPP* remains negatively associated with product disclosure after we control for *LLMComp* and *Fluidity*.

We then use Merkley's disclosure measure and the frequency of MEF as dependent variables in separate analyses. We find that *TPP* is significantly negatively associated with Merkley's measure. The fact that we obtain similar findings when the dependent variable is product disclosure or Merkley's disclosure measure suggests that our product-disclosure measure and Merkley's measure capture similar constructs. In contrast, *TPP* is not associated with the frequency of MEF. One may argue that MEF is unrelated to technological competition because earnings are aggregate measures of performance and reveal nothing about technological investments. This argument would predict no association between *TPP* and MEF. The contrast between the negative association of *TPP* with product disclosure and the lack of association with MEF suggests that researchers cannot simply pair measures of competition and disclosure and expect a negative relation. The relation should be negative only if the type of disclosure is highly relevant to the firm's rivals in that specific area of competition and, therefore, is in alignment with that dimension of competition.[5]

We conduct several supplementary analyses. First, we use alternative measures of product disclosure, including the number of product-disclosure press releases issued during a firm-year and finer classifications of these releases to focus on R&D stage, product introduction, and product improvement. We find consistent associations between *TPP* and product disclosure across these alternative measures. Moreover, the economic effect of *TPP* on product disclosure is largest at the R&D stage, suggesting that information at this stage is most proprietary.

[5] As we illustrate in the framework in Appendix 1, proprietary disclosure costs have three elements: (1) alignment, (2) intensity of competition, and (3) amount of disclosure. Our study addresses all three elements.

We were concerned that our findings might be spurious due to omitted correlated variables. To address this concern, we examine cross-sectional variation in the association of *TPP* and product disclosure across subsamples partitioned by the technology factor, customer concentration, and firms' life-cycle stages. We expect the association to be more negative for high-tech firms, less negative for firms with dispersed customers, and more negative for firms in the early life-cycle stages. Our results are consistent with these expectations. In addition, we provide instrumental-variable estimations to further alleviate the endogeneity concern. We use two regulatory events—the introduction of state-level R&D tax credits and the enactment of the Uniform Trade Secrets Act—to construct instrumental variables. Both events promote R&D activity by firms headquartered in the affected states and both result in exogenous changes to a firm's *TPP*. We continue to find a negative relation between *TPP* and product disclosure.

Our study contributes to the accounting literature by demonstrating the importance of understanding the multidimensionality of competition and disclosure. The relation between competition and disclosure has generated substantial interest among archival researchers. In the Top 5 accounting journals, we found 46 studies examining this relation or controlling for it, most of which were published after 2000.[6] Among them, 16 use MEF as voluntary disclosure, seven use segment reporting, and 23 use other disclosure types. These studies use measures of competition as proxies of proprietary disclosure costs, and the vast majority of the measures are calculated at the industry level: 24 use industry concentration ratios, eight are based on R&D or capital expenditures, seven use industry profitability, and seven use other measures (e.g., survey and firm size). The empirical evidence of the relation between competition and disclosure is mixed.

[6] The journals are *The Accounting Review, Journal of Accounting Research, Journal of Accounting and Economics, Review of Accounting Studies,* and *Contemporary Accounting Research.* We conducted the survey in February 2016.

Given the multidimensionality of competition and disclosure, however, one should not expect a negative empirical relation between *any pair* of competition and disclosure measures. For example, if researchers are interested in a firm's competition in securing reliable and low-price suppliers, the amount of inventory-related disclosure is expected to have a negative relation with the intensity of this competition, but the firm's disclosure of finished-product distributions may have no relation with this competition. Much of prior research uses MEF as a "general purpose" measure of voluntary disclosure perhaps due to data availability. Although some researchers have expressed doubts about this approach, we provide the first evidence against this approach (Lang and Sul 2014). We demonstrate that product disclosure has a negative empirical relation with the intensity of technological competition; in contrast, no relation is found for MEF. Future research on competition, disclosure, and proprietary costs should clearly specify what dimension of competition is of interest, what type of disclosure is relevant to that dimension of competition, and how proprietary disclosure costs occur in that setting.

Our study also contributes to the accounting literature by introducing a measure of technological competition. Our measure is firm-specific and accommodates multi-industry firms, which account for about one-third of US firms. Our measure may be used in future research to examine the effects of technological competition on other corporate decisions.[7]

II. PRIOR RESEARCH

Product-market Competition

The economics literature on competition starts by assuming perfect competition, a state maintained by the free entry and exit of companies. Under this assumption, all products are perfectly substitutable and no firm can influence the price of products. The literature then moves

[7] We distinguish our measure from technology spillover-related measures in Section VI.

on to imperfect competition, under which monopoly and oligopoly may exist and firms compete through production quantity (the Cournot model, Cournot 1838), price of products (the Bertrand model, Bertrand 1883), product differentiation or quality (the Hotelling model, Hotelling 1929), inputs and distribution channels (Stahl 1988), product diversity/portfolio (Dixit and Stiglitz 1977), and technology (Schumpeterian competition, Schumpeter 1934 and 1957). We surveyed 11 top economics, finance, and accounting journals from 1930 to early 2017 and found 219 theoretical studies.[8] Competition in price accounts for 23.3% of the studies, competition in product differentiation/quality 12.8%, quantity 11.9%, inputs and distribution channels 5.5%, product diversity/portfolio 6.8%, technology 10%, and general definitions of competition account for 29.7%.[9] Thus, product-market competition has attracted considerable academic interest, and theorists have focused on multiple dimensions of competition.

Technological competition has its foundation in the concept of Schumpeterian competition (Schumpeter 1934, 1957; Futia 1980). Firms engage in R&D in pursuit of new products and processes to acquire future product-market power. This process of "creative destruction" alters industry structure through successful product and process innovations. In a dynamic model, Futia demonstrates that firms undertake R&D projects to acquire a decisive competitive advantage over their rivals. The barriers generated by R&D investments result in increased concentration in the industry. The ensuring economic rents then attract imitators and new entrants to the industry, which erode the original firms' advantages and economic rents *unless these firms continue to innovate*. The idea of technological competition has drawn increased academic interest in recent

[8] These journals are *Econometrica, American Economic Review, Journal of Political Economy, Quarterly Journal of Economics, Review of Economic Studies*, *Journal of Finance, Journal of Financial Economics, Review of Financial Studies, The Accounting Review, Journal of Accounting Research,* and *Journal of Accounting and Economics.*
[9] Some of the studies model more than one dimension of competition.

years as the US economy evolves into a knowledge-based economy (Aizcorbe 2005; Cantner, Gaffard, and Nesta 2009; Weeds 2002; Wersching 2010).

Due to data limitation, we cannot empirically examine the dynamic process in which technological competition plays a key role. We advance the accounting literature by introducing a firm-specific measure of technological competition and raising researchers' awareness of the role of technological competition in managers' disclosure decisions.

Economic Theories about the Relation between Competition and Disclosure

The classic unraveling theory, which predicts full disclosure by firms, assumes that disclosure is costless and has no externalities (Grossman 1981). All subsequent economic theories about the relation between product-market competition and capital-market disclosure assume some externalities of a firm's disclosure to its product market (Jin 2005). Most often, the externalities come in the form of proprietary disclosure costs. Proprietary costs in theoretical models, however, are rather abstract. Verrecchia (1983) simply assumes constant proprietary costs for all disclosing firms and shows that the likelihood of voluntary disclosure decreases as such costs increase. Later theorists endogenize proprietary costs in a Cournot or Bertrand game and show that managers' equilibrium disclosure strategies depend on the nature of competition (Darrough and Stoughton 1990; Darrough 1993; Wagenhofer 1990). Even though "the results offered are highly sensitive to specific model assumptions," the key message is that managers must trade off the benefits and costs in the capital market vs. the product market (Verrecchia 2001, 146). Note that these studies only model one dimension of competition and one type of disclosure within a model, thereby assuming that the type of disclosure is relevant to that dimension of competition under examination and therefore in alignment.

Empirical Research on the Relation between Competition and Disclosure

Empirical examinations of the relation between competition and disclosure face several challenges. First, the theories are so abstract that it is infeasible to directly test a particular theory (Dedman and Lennox 2009). Most empirical research has instead used Verrecchia's (1983) prediction of a negative relation as a starting point. We take this approach.

Second, competition is multifaceted, and the relation between competition and disclosure may depend on the dimension of competition of interest.[10] Firms may use different strategies and face different rivals in different areas of competition. For example, Amazon competes with Walmart for customers and distribution channels but competes with Google in information technology. In another example, Intel competes with ARM in CPU architecture design but competes with Samsung in mobile CPU sales. It might not be prudent for researchers to assume that evidence obtained for one dimension of competition automatically applies to others.

Third, firms may provide various types of voluntary disclosure. The 170 empirical studies on voluntary disclosure in the 11 top economics, finance, and accounting journals examine MEF (26.5%); other accounting numbers-related disclosure (17.1%); ratings by analysts (8.8%); segment reporting (8.2%); MD&A, risk disclosure, and other 10-K–based textual analyses (8.8%); press releases (6.5%); conference calls (7.6%); internal control-related disclosure (5.9%); compensation disclosure (5.3%); environmental and social responsibility disclosure (5.3%); 8-K filings (2.4%); and other (3.5%).[11] Note that some of these studies examine more than one type of disclosure. Empirical findings for one type of disclosure may not generalize to other types.

[10] Researchers mainly use measures of industry structure as proxies for competition. Among the 54 empirical studies of competition in the 11 top economics, finance, and accounting journals, 76% use measures of industry structure. For example, 42.6% of the 54 studies use industry concentration ratios. Raith (2003, 1430) comments that industry concentration ratios are "poor measures of competition unless it is clear what causes their variation."

[11] Earlier studies examine the relation between competition and segment reporting and document mixed findings (Beyer et al. 2010). Verrecchia and Weber (2006) find that firms in a more competitive environment are more likely to redact information from SEC filings.

Several studies have examined the relation between competition and MEF. Bamber and Cheon (1998) conclude that when proprietary costs are high, managers provide less precise MEF and disclose MEF at private meetings with reporters and analysts instead of a public venue (e.g., press releases and shareholder meetings). Li (2010) reports a negative association between existing competition and MEF frequency and a positive association between entrant competition and MEF frequency. Ali, Klasa, and Yeung (2014), however, find that MEF are less frequent and have shorter horizons in more concentrated industries. Given that Li (2010) interprets high industry concentration as low competition, Ali et al.'s results contradict Li's.

The final challenge is that the competition measures used in most prior research are at the industry level. Industry-level competition measures have three problems. First, within a given industry, the few largest firms likely face different levels of competition than do the remaining firms. Second, it is inherently difficult for industry-level competition measures to explain variation in voluntary disclosure at the firm level. Third, these competition measures use the membership of a firm's *primary* industry and do not capture the competitive environments of the large proportion of US firms that operate in multiple industries.

Our study takes the multidimensionality perspective. As illustrated in Appendix 1, we believe that the link between competition and disclosure is proprietary disclosure costs, which have three elements. The first element is the alignment of the type of disclosure with the dimension of competition under examination. Without this alignment, disclosure is not useful to the disclosing firm's rivals and therefore incurs no proprietary costs regardless of the intensity of competition and the amount of disclosure. The second element is the intensity of competition. As competition intensifies, a given piece of information will invite more damaging actions by the disclosing firm's rivals and, therefore, increase proprietary costs. The third element is the amount of disclosure. As this amount increases, the amount of proprietary information increases and, therefore, proprietary costs increase. We extend the accounting literature by addressing all three elements.

III. SAMPLE AND MAIN VARIABLE MEASUREMENTS

Sample

Our sample selection begins in 2002, before which the Capital IQ coverage was too limited for us to identify disclosure events, and ends in 2012, because we need to observe firms' external financing in subsequent years. We start with 42,710 firm-year observations from North America Compustat and exclude 1,685 firm-years in financial services (SIC 6000–6999) and utilities (SIC 4900–4999). We drop another 7,306 firm-years with no data available for control variables, most of which require the previous year's data. We also exclude 13,512 firm-years that have no R&D investments in recent years (i.e., zero R&D stock).[12] Our final sample has 20,207 firm-years. Table 1 summarizes the sample selection.

Technological Peer Pressure

Variable Construction

Our measure of *TPP* derives from the technology-based product-market rivalry variable in Bloom et al. (2013). The idea behind their variable is that a sample firm's technological threat comes from its peers' technological advances proxied by R&D investments. Bloom et al.'s variable for firm i in year t has two components: (1) a peer j's R&D stock in dollars at the end of year t, denoted as $G_{j,t}$, and (2) the closeness of peer j to sample firm i, ω_{ij}, representing the weight used to aggregate threats from multiple peers. Because R&D investments benefit a firm over multiple years, following Jaffe (1986), Bloom et al. count not only a firm's R&D investments in the most

[12] If we include firms with zero R&D stock but fill the variable with the minimum value of the firms' primary industry members' R&D stock, our sample size is 29,743 and *TPP* remains significantly negative at the 1% level.

recent year but also those in preceding years assuming a decay rate of 15%: $G_{j,t} = R\&D_{j,t} + (1-15\%)\, G_{j,t-1}$, where $R\&D$ is the R&D expense reported for year t.

The closeness, ω_{ij}, is calculated in the *product-market space* spanned by 4-digit SIC industries in which either firm i or j operates according to Compustat's Segment database. The more overlapping industries between the two firms, the higher the closeness. Additionally, the higher the proportions of each firm's segment sales in the overlapping industries, the higher the closeness. To illustrate this point, consider two firms, i and j, and three industries, A, B, and C. In the first case, each firm generates two-thirds of its sales from industry B, one-third from industry C, and none from industry A. In the second case, firm i generates two-thirds of its sales from industry B and one-third from industry C, whereas firm j generates one-third of its sales from industry B and two-thirds from industry C. In the third case, industry B accounts for four-fifths of firm i's sales and only one-fifth of firm j's sales; the other one-fifth of firm i's sales come from industry C and the other four-fifths of firm j's sales come from industry A. The two firms are closest in Case 1 and least close in Case 3. If the two firms do not overlap in any industry, then firm j is not a peer of firm i at all.

	Case 1				Case 2				Case 3		
Industry	A	B	C		A	B	C		A	B	C
Firm i	0	2/3	1/3		0	2/3	1/3		0	4/5	1/5
Firm j	0	2/3	1/3		0	1/3	2/3		4/5	1/5	0

Bloom et al. (2013) formally calculate ω_{ij} in Equation (1) by taking the cosine of the two firms' vectors (V_i and V_j) with the k^{th} element of each vector equal to the firm's proportion of its total sales in the previous two years in industry k, where K is the total industry count.[13] The cosine of the vectors (angle θ) has a geometrical interpretation as the similarity of the two vectors.

$$\omega_{ij} \equiv \cos(\theta_{ij}) = \langle \frac{V_i}{\|V_i\|} \cdot \frac{V_j}{\|V_j\|} \rangle = \frac{\sum_{k=1}^{K} v_{ik}\, v_{jk}}{\sqrt{\sum_{k=1}^{K} v_{ik}^2}\sqrt{\sum_{k=1}^{K} v_{jk}^2}} \tag{1}$$

Bloom et al. (2013) multiply a peer's R&D stock, $G_{j,t}$, by the weight ω_{ij} and then sum up the products across all peers. They use the logarithm of this sum in their empirical analyses.

We modify their variable by dividing this sum by the firm's own R&D stock $G_{i,t}$. *TPP* for firm i at the end of fiscal year t is calculated as:

$$TPP_{i,t} = \log[1 + (\textstyle\sum_{j \neq i} \omega_{ij} \times G_{j,t})/G_{i,t}] \tag{2}$$

The numerator of the ratio inside the bracket (hereafter, "the numerator") is the pool of peers' R&D stock in dollars, representing the threats of rivals' technological advances.[14] The denominator is the sample firm's own R&D stock, representing its technological preparedness. *TPP* represents the threats of rivals' technological advances relative to the firm's own preparedness. For example, a ratio of 10 means that a firm's peers collectively invest $10 in R&D activities while the firm itself invests $1. After the logarithm, the *TPP* of our sample firms is well distributed with a mean of 4.299, median of 4.552, and the standard deviation of 2.522 (see Panel A of Table 2). The mean of 4.299 means that on average, peers invest $72.6 in R&D for every dollar of R&D investment by the sample firm.

Reasons for the Modification

We modify Bloom et al.'s (2013) variable by dividing it by a firm's own R&D stock for economic and econometric reasons. Conceptually, two firms experience different competitive

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[13] Bloom et al. (2013) use sales from the entire sample period to calculate the weight. Qiu and Wan (2015) use sales from the previous five years. We use sales from the previous two years to better reflect fast changes in the product-market landscape of R&D firms.

[14] The pool of peers' R&D stock is zero for 1,605 of our 20,207 firm-year observations. We add the number of 1 to the ratio in the bracket to retain these observations.

pressure if their preparedness differs, even if they face the same threat: the firm with low technological investments faces stronger pressure than the other firm that has invested a lot in technology. For example, a technological breakthrough made by Samsung will have different consequences for Apple, which is technology savvy, than for Motorola, which is not. Jaffe (1986, 995) indeed finds that the same technological pool—the numerator—has different effects for firms with high R&D stock vs. those with low R&D stock.

Firms facing the same threats from rivals' technological advances may vary substantially in their own preparedness. In Panel A of Appendix 2, we sort sample firm-years independently into deciles by the numerator and the denominator and report the mean value of *TPP* as well as the number of observations for each group. Within each decile of the numerator, the denominator varies substantially and vice versa. Take the example of Decile 5 of the numerator. The observations distribute quite evenly in all deciles of the denominator. Thus, firms with similar threats from peers' technological advances may range from being not prepared, to being somewhat prepared, to being very prepared.

Our modification is also made for an econometric reason. If only the numerator is used, the variable is not stationary: the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test rejects the null of stationarity for 95.3% of firm time series at the 5% significance level. Nonstationarity might result in inconsistent coefficient estimates in regressions (Levin, Lin, and Chu 2002).

Benefits of TPP over Traditional Industry-based Competition Measures

TPP better captures competition than the commonly used industry structure-based competition measures. The strength of our *TPP* measure is evident in the following example. Hewlett-Packard (HP) and International Business Machines (IBM) are two tech behemoths competing head to head. HP reports sales in each of IBM's four industry segments. A commonly used competition measure, such as the Herfindahl index (*HHI*), would *not* identify the rivalry between HP and IBM because HP's primary SIC code is 3570 (Computer and Office Equipment) and IBM's is 7370 (Services-Computer Programming and Data Processing). By contrast, our measure considers all industries in which a firm operates.

Our *TPP* measure can also reflect competition intensity in a timely matter. *TPP* is updated annually for the R&D investments in the year that has just ended and for firms' closeness using newly available segment sales. For example, from 2000–2011, HP and IBM's closeness, $\omega(\mathrm{HP}, \mathrm{IBM})$, hovered around 45%. In 2013 (outside of our sample period), it jumped to 60% as HP substantially increased its presence in the two leading industry segments of IBM—computer-related services (SIC=7379) and prepackaged software (SIC=7372). This change was partly due to HP's turnaround effort (initiated in 2012) to transform itself into an IBM-like provider of computing services.[15] In particular, HP introduced a comprehensive cloud strategy and a number of related software products and services. HP's strategic move has made it a closer rival to IBM. As a result, HP's technological investments would present a greater threat to IBM. Our measure captures this change in competition.

Descriptive Statistics of TPP

In Panel B of Appendix 2, we provide descriptive statistics of *TPP* for the Top 20 industries ranked by the number of sample firm-years. Prepackaged Software has the most observations and the highest *TPP*. Semiconductors and Related Devices has the third most observations and the second-highest *TPP*. Computer Integrated Systems Design has the third-highest *TPP*. We report

[15] "HP reins in revenue slide as turnaround progresses." Edwin Chan, *Reuters*, February 21, 2014. HP's management fully recognized the importance of R&D as a key factor in determining the success of its strategic shift and announced a three-year R&D program when it unveiled the turnaround plan in 2012.

within-industry standard deviations in the last column and observe reasonable variation in *TPP* *within* industries.

In Panel C we present the distribution of *TPP* for each sample year. For each year, we calculate the standard deviation of *TPP* within each industry and report the mean. The numbers suggest that the reasonable variation in *TPP* within industries observed in Panel B is not driven by particular sample years. We report cross-industry variation in *TPP* in the last column and also observe reasonable variation *across* industries.

In Panel D we present the transition matrix of *TPP* decile assignments from the previous year to the current year. The percentage of firms that remain in the same decile ranges from 75.6% to 91.2%. The persistence of *TPP* from one year to the next is not surprising given that we use rolling windows in collecting R&D and industry-segment sales.

Technological Peer Pressure and Future Performance

Competition causes the returns on existing investments to mean revert (Stigler 1963, 54). In Panel A of Table 3 we regress future performance measures on *TPP* and control for existing performance and the standard deviation of performance in recent years (as a proxy for business risk). The performance measures, each averaged in the current year and the next two years, are: (1) accounting return on assets, adjusted for the industry median, (2) percentage change in sales, and (3) market share in the firm's 4-digit SIC primary industry. The coefficient on TPP_{t-1} is significantly negative in each regression, suggesting that firms under higher technological pressure experience poorer future performance, consistent with the prediction of economic theories.[16]

[16] Li et al. (2013) regress the change in return on net operating assets (RNOA) from the current year to the next year on their competition measure and the interaction of the competition measure and existing RNOA. They find a negative coefficient for the interaction and interpret it as an effect of competition on diminishing returns. We do not find this effect (untabulated).

We modify the above tests for the context of technological competition by using the direct outcomes of R&D investments as a performance measure. The first measure is the total number of patents granted in the current year and the next two years. The second measure is the estimated dollar value of those patents according to Kogan, Papanikolaou, Seru, and Stoffman (2017). We expect firms under higher technological peer pressure to have less success in subsequent patents because of their constrained resources relative to their peers'. Panel B of Table 3 presents the estimation results, consistent with this expectation.[17] The findings in Table 3 provide comfort that our *TPP* measure captures technological competition.

Product Disclosure

Examples of Product Disclosure

Product disclosure contains information that can benefit competitors in technological competition.[18] One example is pharmaceutical companies' decades-long effort to find drugs that may treat Alzheimer's disease.[19] In March 2015, Biogen released detailed data from a study of 166 patients who were taking its drug aducanumab, which aimed to remove amyloid plaques that had accumulated in the brains of Alzheimer's patients. Biogen's product disclosure offered encouraging signs for its drug and revealed key components of its clinical trial, including dose levels and the targeted patient population (e.g., the earlier-stage cohort). In April, following Biogen's disclosure, Roche revived its two compounds (gantenerumab and crenezumab), which provided the same plaque-removing therapy as Biogen's medicine but had previously been deemed

[17] The untabulated results are similar if we also control for a firm's R&D stock scaled by its total assets measured at the end of year *t*-1. This control variable has a positive coefficient.
[18] Even though intellectual property laws provide disclosing firms some protection, disclosure when patents are pending can still incur proprietary costs.
[19] Despite billions of dollars poured into related research, the Alzheimer's disease treatment effort remains a graveyard for a large number of promising drugs. A total of 244 chemical compounds were developed and tested for Alzheimer's disease in 413 clinical trials between 2002 and 2012, and they all failed (Cummings, Morstorf, and Zhong 2014).

statistically futile. Notably, with the thought "if Biogen's drug works, so should Roche's" in mind, Roche decided to revise its dose levels and target the same earlier-stage patient group as in Biogen's trials.[20] Interestingly, Biogen's own trial, particularly in patient selection, had also benefited from Eli Lilly's failed solanezumab, which was developed based on the same drug mechanism and showed signs of efficacy among patients in the earlier stages of Alzheimer's even though it missed its overall goals.

In Appendix 3 we present an example of a product-disclosure press release. IBM's disclosure reveals a future 2-year research collaboration plan with the FDA to exploit blockchain technology in the healthcare industry, including research objectives, research scope, the technology involved, and potential targeted areas. Such information can be used by IBM's competitors. For example, Accenture in the technology consulting industry, Global Arena Holding in the blockchain technology area, and Internet of Things (IoT) companies such as Google and Cisco may follow IBM in developing new technologies, devices, and consulting services for the healthcare industry that utilize blockchain technology.

Is Product Disclosure Perceived to Contain Proprietary Information?

Disclosure research has often assumed whether a type of disclosure has proprietary information, but no study has empirically validated these assumptions. Such validations are difficult because researchers do not observe managers' internal deliberations and do not observe what peers do with the disclosed information. We perform two procedures to help understand what information is proprietary and how much proprietary information that product disclosure contains.

[20] See "Biogen gives Roche 'renewed confidence' in its own failed Alzheimer's drugs" and "Roche takes another shot at Alzheimer's after Biogen success" at http://www.fiercebiotech.com/story/biogen-gives-roche-renewed-confidence-its-own-failed-alzheimers-drugs/2015-04-22 and http://www.bloomberg.com/news/articles/2015-06-09/roche-takes-another-shot-at-alzheimer-s-after-biogen-has-success.

We focus on computer/technology related industries because of the availability of our participants. In the first procedure we interview three experts in these industries. In the second procedure we survey participants on Amazon Mechanical Turk.

Interviews

We conducted independent phone interviews with two engineers with five and 10 years of working experience, respectively, and one academic with eight years of research experience. All of these professionals work in the computer/technology-related industries. We provided each interviewee a recent product-disclosure press release by a company in their field before the phone interview and asked them to assess whether and what information in the press release was useful to the disclosing firm's rivals. We also asked the two industry experts whether and how their firms monitor their peers. A summary of their approved notes is available upon request.

Each interviewee pointed out specific paragraphs or sentences in the press release that would be useful to the disclosing firm's rivals. They also pointed out paragraphs that exhibit common sense and thus have no proprietary content. Interviewee 1 distinguished information about the direction of R&D activity from the technical information contained in the press release. He commented that (1) the former is more common and is especially helpful to firms that have resources and can act fast and (2) the latter gives rivals information (or directs them to sources) about how to implement the disclosed technology. Furthermore, one damaging action rivals can take is stealing talent involved in developing the disclosed projects or products. Interviewee 2 confirmed Interviewee 1's point that most of the proprietary information in the product-disclosure press release is about the direction of future R&D. In addition, he mentioned that one targeted audience of product disclosure is future buyers and that the disclosing company must weigh the costs of assisting its rivals for the benefits of generating buzz among buyers. The first two interviewees stated that their firms regularly monitor news about their rivals, including product-disclosure press releases, patents, media discussion, and academic papers written by individuals affiliated with their rivals. Interviewee 3 echoed the main message of Interviewees 1 and 2.

<u>Experimental Survey</u>

Farrell, Grenier, and Leiby (2017) find that Amazon participants are suitable for certain experimental tasks. The authors observe that Amazon participants have higher financial literacy than the general public and perform especially well on tasks in which they have an intrinsic interest, such as computer-related tasks. Thus, we design an experimental task for participants to assess the amount of proprietary information contained in product-disclosure vs. MEF press releases. We include MEF press releases to provide a benchmark for us to evaluate the level of proprietary content in product disclosure.[21]

We largely follow the procedures for Experiment 2 in Bonsall, Leone, Miller, and Rennekamp (2016), who validate their measure of readability of 10-K reports using Amazon participants. We hired 206 participants who passed the financial literacy (a standard survey used in prior research) and computer/technology knowledge (a survey of five questions) screening and completed our experimental survey (a total of 459 attempted the task, including the screening surveys, so the completion rate was 44.9%). Each participant was given a product-disclosure (PD) press release *and* an MEF press release with the order of the presentation being random. The product disclosure or MEF disclosure was each randomly selected from three documents to increase the generalizability of our finding. The six documents were real press releases of similar length issued by computer/technology companies in the first 60 days of 2017, with the company

[21] We have obtained the approval of the Institutional Review Board from our respective institutions for conducting this experiment.

names replaced with fake names.[22] *Score* $_{PD\text{-}MEF}$ is the difference in the ratings of proprietary information for product disclosure vs. MEF. We include a validation question and exclude 18 responses that failed this check.

Appendix 4 reports that on average, participants viewed product disclosure as containing something between "a little" and "some" proprietary information and viewed MEF as containing something between "not at all" and "a little" proprietary information. *Score* $_{PD\text{-}MEF}$ has a mean of 0.569, significantly positive at the 1% level. We break down the responses by demographic information and find that groups that assess significantly higher proprietary content of product disclosure than MEF are participants with higher education, either no working experience in computer/technology or more than 10 years of experience, and either no managerial experience or 5-10 years of experience. *Score* $_{PD\text{-}MEF}$ remains significantly positive after we control for participants' demographic information (untabulated). Thus, financially literate individuals with extensive computer/technology knowledge perceive product disclosure to contain significantly more proprietary information than MEF.

Measure of Product Disclosure, Market Reaction, and Descriptive Statistics

Capital IQ collects corporate events and classifies them into about 150 categories. We define a product-development related event as one classified by Capital IQ in the category of "Announcements pertaining to the introduction, change, improvement, or discontinuation of a company's product or services" ("This includes all announcements from the research to final launch of the product and any enhancements to the product after launching").[23] We obtain the

[22] We use recent press releases to avoid participants' hindsight bias (Thaler 2015, 22).
[23] Product disclosure is voluntary. If firms file an 8-K report after the press release, they almost always file it under Items 7.01 and 8.01, which are considered voluntary items for 8-K filings. Although stock exchange rules stipulate that firms should immediately release material information, firms have leeway not to do so because of the vague

actual press releases from Thomson Reuters News Analytics. To ensure that the press releases were issued by the firm, we required that (1) the news be released via a newswire such as *PR Newswire* and *Business Wire*, (2) the company's name appear in the headline of the press release, and (3) the company's name appear in the first five words of the body of the press release. We randomly checked 50 press releases in our sample and confirmed that they were indeed released by the firms. We obtained 240,663 product-disclosure press releases with Compustat identifiers issued by 56,326 firm-years, including international and over-the-counter stocks, during 2002–2012. After merging with our 20,207 firm-years collected in Table 1, we are left with 85,929 press releases from 2,321 unique firms. About 59.7% of our sample firm-years provide product disclosure and the mean (median) number of these firms' press releases is 4.6 (1). The disclosure of R&D activity and product introduction is more frequent than that of product improvements; product retirement disclosure is infrequent.

In general, we expect investors to react positively to product disclosure. Product disclosure tends to be good news because managers do not have incentives to voluntarily disclose bad news. Even when the news is neutral, the disclosure may reduce investors' *uncertainty* about whether and how a firm takes actions to maintain its position in the product market. In Panel A of Table 4 we present the size-adjusted stock returns on the day of or within the three-day window, [-1, 1], of a product-disclosure press release. Consistent with our expectation, the return reactions to product disclosure are significantly positive. For the one-day return, the mean of 0.326% is much larger than the median of 0.033%, suggesting the existence of extremely large positive returns. In Panel

criterion of "materiality." In fact, the New York Stock Exchange even states, "Premature announcements of new products whose commercial application cannot yet be realistically evaluated should be avoided, as should overly optimistic forecasts, exaggerated claims and unwarranted promises." The Food and Drug Administration Modernization Act (1997, Sec. 113) mandates registry of new drug application trials for serious and life-threatening diseases or conditions, but does not require registry of early stage trials (e.g., Phase I trials), press releases of any clinical trials, or disclosure of clinical trial results.

B we regress returns on the logarithm of the total number of words in a press release and find that the word count is significantly positively associated with returns, suggesting that the word count can proxy for the amount of information contained in a press release.

For our primary analysis we measure the product disclosure of a firm during fiscal year *t*, *PDwords,* by the total word count of its product-disclosure press releases after excluding common stop words (e.g., the, of, to) and removing the last paragraph of the company's description from the press releases. The sample mean (median) of *PDwords* is 1,142 (152). Panel A of Figure 1 plots the distribution of *PDwords* for the disclosing firms. The minimum is 35 words, and the first bar represents 34.5% of the disclosing firm-years with *PDwords* below 500 words.

IV. PRIMARY ANALYSIS

Comparing *TPP* with Alternative Firm-specific Competition Measures

We compare *TPP* with two alternative firm-specific competition measures. *LLMComp* is the number of competition-related words (i.e., compete, competing, competition, competitor, and competitive) in a firm's 10-K report divided by the total number of words in the report, expressed as one per 1,000. The measure captures "the broadest notion of competition" as perceived by management and "has the advantage of capturing competition from many different sources that are hard to identify empirically" (Li et al. 2013, 401 and 402). We follow Li et al.'s procedures and construct *LLMComp* for our sample period. The mean (median) of *LLMComp* is 1.190 (1.108), higher than the statistics reported in Li et al.'s Table 1 but similar to those in Peterson and Tran (2014).[24]

[24] We obtain the *LLMComp* measure from Feng Li's website (http://webuser.bus.umich.edu/feng/) for 2003–2009—the overlapping sample years of Li et al. (2013) and our study—and find a Spearman correlation of 0.54 between their measure and our measure. We have contacted coauthors of Li et al. to reconcile the differences. The coauthor who responded to us kindly brought Peterson and Tran (2014) to our attention and advised that the differences are likely due to noise in the denominator (e.g., whether certain selections of the 10-K or numbers in tables are included).

Hoberg et al. (2014) introduce *Fluidity* as a measure of the competitive threat faced by a firm in its product market. J_t is the number of unique words used in the business descriptions (Item 1) of the 10-K report of all firms in fiscal year t. $W_{i,t}$ is a vector of dimension J_t, with element j taking the value of 1 if firm i uses word j in its business descriptions and 0 otherwise. $NW_{i,t}$ denotes the vector of $W_{i,t}$ normalized to unit length. $D_{t-1,t}$ is defined as $|\sum_i (W_{i,t} - W_{i,t-1})|$, capturing the *absolute* changes in all firms' use of each word in year t from the previous year. $ND_{t-1,t}$ denotes the normalized vector of $D_{t-1,t}$. *Fluidity* is the dot product of *NW* and *ND*:

$$Fluidity_{i,t} = NW_{i,t} \cdot ND_{t-1,t} \tag{3}$$

Hoberg et al. (2014) argue that by calculating the cosine similarity between a firm's own word-usage vector and the absolute aggregate change in all-firms'-word-usage vector, they measure the changes in a firm's product space due to moves made by its competitors. The authors interpret a higher competitive threat when rivals describe their business as *either more similar or less similar* than the sample firm's. We believe that a firm faces a lower level of threat when rivals describe less-similar business. We obtain the *Fluidity* measure for our sample period from the authors' website of http://hobergphillips.usc.edu/industryconcen.htm.

In Table 5 we compare *TPP* with *LLMComp* and *Fluidity*. The Spearman correlations of *TPP* with *LLMComp* and *Fluidity* are both significantly positive at 0.139 and 0.126, respectively. In Panel B we sort sample firms into quintiles by *TPP* and report the mean values of *LLMComp* and *Fluidity* for each quintile. The values of *LLMComp* and *Fluidity* of the highest *TPP* quintile are significantly higher than those of the lowest quintile, confirming the positive correlations of *TPP* with *LLMComp* and *Fluidity*. The positive but rather low correlations of *TPP*, *LLMComp*, and *Fluidity* suggest that these measures capture different aspects of product-market competition. *TPP* is intended to capture technological competition, whereas *LLMComp* captures managers' perception of competition from many sources and *Fluidity* captures how rivals change their business descriptions either toward or away from the sample firm's.[25]

Comparing Product Disclosure with Alternative Voluntary Disclosure Measures

We compare our measure of product disclosure with two alternative measures of voluntary disclosure: one is a close alternative to our measure and the other is quite different from ours. Merkley (2014) counts the number of sentences that contain at least one keyword related to R&D in the 10-K issued by a firm that reports R&D investments. Although he uses the label "R&D disclosure," his list of keywords includes "product development," "developing new products," "product candidate," etc. Thus, his disclosure measure captures what we refer to as product disclosure.[26] We follow Merkley's procedures, use his keyword list, and construct his measure for our sample period. We refer to this measure as *Merkley*. The measure has a mean (median) of 26.3 (14) R&D–related sentences in a 10-K report, whereas Merkley reports the mean (median) of 30.9 (20) for his sample period of 1996-2007. *Merkley* is positive for 80.6% of our sample. Panel B of Figure 1 plots the distribution of *Merkley* for the disclosing firms.

The other alternative measure of voluntary disclosure is the frequency of MEF for fiscal earnings issued by a firm during fiscal year *t*. We refer to the frequency of MEF as *MEFFreq*. This measure is positive for 24.3% of our sample. Panel C of Figure 1 plots the distribution of *MEFFreq* for the disclosing firms.

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[25] Note that *LLMComp* and *Fluidity* are based on a firm's disclosure in the 10-K. Such disclosure might be related to the firm's subsequent disclosure of R&D, product development, and MEF because all these disclosure decisions are made by the same management. Thus, *LLMComp* and *Fluidity* might not be ideal measures of competition in testing the relation between competition and disclosure even though they could be useful in other settings.

[26] Merkley's (2014) disclosure differs from our product disclosure in two respects. First, his disclosure is provided at the very end of the reporting cycle for a fiscal year, whereas our disclosure is more timely. Second, Merkley's disclosure is contained in a regulatory filing that faces higher scrutiny than a press release that contains our disclosure. Managers may be less open but more credible when making Merkley's disclosure than ours.

We compare our product disclosure measure with *Merkley* and *MEFFreq* in Table 6. The Spearman correlations of product disclosure with *Merkley* and *MEFFreq* are both significantly positive. This observation is unsurprising because management's attitude toward transparency is key to a firm's overall voluntary disclosure. The Spearman correlation between product disclosure and *Merkley* is as high as 0.288, suggesting that firms that provide product disclosure early tend to discuss their R&D activities later in the 10-K report. The correlation of product disclosure with *MEFFreq* is much lower at 0.038, suggesting that product disclosure and MEF are distinct types of voluntary disclosure. Panel B of Table 6 reports the mean values of *Merkley* and *MEFFreq* for the group with zero product disclosure and for five quintiles with positive product disclosure. The pattern is consistent with the correlation table.

Associating Competition Measures with Product Disclosure

The multidimensionality of competition means that even though economic theories generally predict a negative relation between competition and disclosure, we should not expect all competition measures to be negatively associated with product disclosure. The negative relation is expected for *TPP* because product disclosure potentially reveals information valuable to the disclosing firm's rivals in technological competition. We estimate Equation (4) and use *Competition* as a placeholder for the three competition measures: *TPP*, *LLMComp*, and *Fluidity*. To facilitate the comparison of the economic effects, we follow Li et al. (2013) and use the decile ranks (between 0 and 1) of the competition measures in regression analyses.[27]

$$Log(1+PDwords_t) = \alpha + \beta\, Competition_{t-1} + \gamma\, PDdum_{t-1} + \text{Other Controls}_{t-1} + \text{industry effects} + \text{year effects} + \varepsilon \qquad (4)$$

[27] Firms are sorted into deciles ranging from 1 to 10 with 10 being the highest each year based on the raw value. The higest group is assigned the value of 1 (i.e., (10-1)/9=1) and the lowest group is assigned the value of 0 (i.e., (1-1)/9=0).

$PDdum_{t-1}$ is 1 if the firm provided product disclosure during fiscal year *t*-1 and 0 otherwise. Among our sample firms, 78.7% (78.9%) of those providing (not providing) product disclosure in the previous year continue the pattern in the current year, suggesting that the *act* of providing or not providing product disclosure is sticky from one year to the next. Among those providing product disclosure in both years, the correlation of the two years' product-disclosure amount is 0.600, which is not as high as the act of disclosure. Thus, we control for the stickiness of a firm's act of providing product disclosure.[28]

The other control variables are similar to Li (2010), based on the determinants of MEF in prior research, and are calculated at the end of fiscal year *t*-1. We control for size, *log(MVE)*, because prior research finds that larger firms tend to provide more disclosure. We control for return volatility, *StdRet*, and earnings variability, *StdEarn*, because Waymire (1985) finds that firms with higher uncertainty are less likely to issue MEF and Lu and Tucker (2012) find that these firms are more likely to provide nonearnings forward-looking information instead. We control for analyst following, *Analysts*, because analysts demand information for their forecasting and stock recommendations. We control for institutional holdings, *IO*, because firms with higher institutional holdings are more likely to provide management forecasts (Ajinkya, Bhojraj, and Sengupta 2005). We control for the market-to-book ratio, *M/B*, because high-growth firms typically have greater information asymmetry, which affects managers' disclosure decisions. We follow Li (2010) and Ali et al. (2014) and control for leverage, *Leverage*. We control for the earnings change, *ΔEPS*, because earnings performance affects managers' decisions to provide MEF (Miller 2002; Houston,

[28] If we control for the previous year's amount of product disclosure, our inferences are similar. We do not use firm fixed effects. Firm fixed effects treat all sample years of a firm equally. For disclosure decisions, however, a firm's previous-year behavior is most relevant to its current-year decision, and its earlier years' behavior is less relevant. Moreover, we are more interested in cross-firm variation than within-firm variation. Firm fixed effects would remove cross-firm variation.

Lev, and Tucker 2010). Last, we control for manager-anticipated external public financing, *ISSUE*, because Frankel, McNichols, and Wilson (1995) find a positive association between external financing and the issuance of MEF. See Appendix 5 for variable definitions.

Finally, we control for industry (4-digit SIC) fixed effects and year fixed effects. We are interested in cross-firm variation *within* an industry-year. We winsorize the continuous dependent and independent variables at the 1% and 99% of the distributions and estimate all regressions with standard errors robust to heteroskedasticity and clustered by firm.[29] Throughout our OLS analyses, we check the VIF index and do not observe multicollinearity.

We report the regression estimations in Table 7. The adjusted R^2 increases visibly from 45.4% in Column 1, which excludes $PDdum_{t-1}$, to 48.2% in Column 2, which includes the variable, suggesting the importance of controlling for a firm's past disclosure behavior. In Column 2, *TPP* has a significantly negative coefficient at -0.593 with a *t*-statistic of -5.12. The economic effect is large: if a firm moves from the lowest *TPP* decile to the highest, it reduces the number of product-disclosure words by about 44.7%.[30] This finding suggests that managers are reluctant to provide product disclosure as *TPP* intensifies, consistent with our expectation.

In Column 3 we use *LLMComp* as the competition variable. The coefficient is not significantly different from 0. In Column 4 the coefficient on *Fluidity* is significantly positive at 0.928. One explanation is that the high values of *Fluidity* of our sample firms are more likely due to peers moving away from the sample firm's product markets than moving toward them. Another explanation is that *Fluidity* captures the threat of new entrants, and firms release information about

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[29] Our test results are similar if we use the robust-regression estimation method (RREG in Stata) instead of OLS. The former is robust to influential observations and to violations of normality in the error term.

[30] Let Y_1 (Y_0) be the number of product disclosure words for the highest (lowest) *TPP* decile. The coefficient of -0.593 on *TPP* means that $Log(1+Y_1) – Log(1+Y_0) = -0.593$. Thus, $(1+Y_1)/(1+Y_0) = exp(-0.593) = 0.553$. So, $(Y_1-Y_0)/(1+Y_0) = - 44.7\%$.

product-development success to discourage entry. The comparisons of coefficients on *TPP*, *LLMComp*, and *Fluidity* suggest that empirical detections of the negative relation between competition and product disclosure require an alignment between the dimension of competition under examination and product disclosure. [31]

One concern about the analysis of *TPP* and product disclosure is that firms with more intensive R&D activity have more information available for disclosure and also have a low *TPP*, resulting in a spurious negative association between *TPP* and product disclosure. Although we have controlled for a firm's previous-year product disclosure behavior to mitigate the concern that some firms have more information for disclosure than other firms, we now directly address the role of R&D intensity in the relation between *TPP* and product disclosure. We construct G_t/TA_t to measure a firm's R&D intensity at the end of year *t*, where *G* is the R&D stock and *TA* is the total assets and serves as a scalar.

In Column 1 of Panel A of Table 8, we reproduce the estimation results of our primary regression. In Column 2 we add *G/TA* but remove *TPP* to observe the effect of *G/TA* alone: *G/TA* is positively associated with the amount of product disclosure, consistent with the expectation that firms with more R&D activity have more information available for disclosure. In Column 3 we include both *TPP* and *G/TA*: after controlling for *G/TA*, *TPP* is still significantly positively associated with product disclosure, suggesting that our primary finding is not spurious. In Panel B, we sort sample firm-years into quintiles based on *G/TA* and estimate our primary model on each quintile. The coefficient on *TPP* is significantly or weakly significantly negative in each quintile and the differences among the five *TPP* coefficients are statistically insignificant (*p*-value = 0.76).

[31] In untabulated results, we additionally control for industry-structure-based competition measures (e.g., the Herfindahl index and the three competition measures in Li 2010). Our findings are robust and these competition measures do not load.

In these regressions, *TPP* is decile-ranked in the full sample; our results barely change if we rank *TPP* within each quintile. We do not control for *G/TA* in subsequent regression analyses because *G/TA* is highly correlated with the denominator in *TPP*. Coefficient estimates in multivariate regressions are partial-out results. Including *G/TA* would complicate the interpretation of the coefficient on *TPP*, which is a ratio by construction.

Associating *TPP* with Alternative Voluntary Disclosure Measures

We modify Equation (4) by replacing the dependent variable with *Merkley* and *MEFFreq*, respectively. In Equation (5) $Merkdum_{t-1}$ is 1 if the firm provided R&D disclosure in its year *t*-1's 10-K and 0 otherwise. The act of providing such disclosure is highly sticky: 98.0% (91.6%) of those disclosing (not disclosing) in the previous year continue the pattern in the current year. In Equation (6) $MEFdum_{t-1}$ is 1 if the firm provided any MEF in year *t*-1 and 0 otherwise. In our sample, 85.7% (85.5%) of those disclosing (not disclosing) MEF in the previous year continue the pattern in the current year.[32] We use a generalized negative binomial model for Equation (6) because *MEFFreq* is a count variable.[33]

$$Log(1+Merkley_t) = \alpha + \beta\ Competition_{t-1} + \gamma\ Merkdum_{t-1} + \text{Other Controls}_{t-1} + \text{industry effects} + \text{year effects} + \varepsilon \quad (5)$$

$$MEFFreq_t = \alpha + \beta\ Competition_{t-1} + \gamma\ MEFdum_{t-1} + \text{Other Controls}_{t-1} + \text{industry effects} + \text{year effects} + \varepsilon \quad (6)$$

Columns 1–4 of Table 9 report the estimations of Equation (5). The coefficient on *TPP* is significantly negative and the coefficient on *Fluidity* is significantly positive. The similarity of the

[32] The amount of Merkley disclosure is highly sticky, too, with the correlation of the previous year's and current year's disclosure amount being 0.953. In contrast, the correlation of *MEFFreq* in these two years is 0.645, less sticky. If we control for last year's disclosure amount in Equations (5) and (6), the results are similar to those in Table 9.

[33] We choose a negative binomial model over Poisson because of over-dispersion (i.e., the variance of *MEFFreq* exceeds its mean). We choose the *generalized* negative binomial over the traditional negative binomial to accommodate varying over-dispersion during our sample period. For example, the popularity of MEF had its highs and lows as the merits of quarterly MEF were debated during our sample period (Houston et al. 2010).

results from estimating Equations (4) and (5) suggests that *Merkley* and *PDwords* capture a similar construct. The coefficient on *LLMComp* is now significantly positive, and we do not have an explanation for this result.

Columns 5–8 report the estimations of Equation (6). *TPP* is not associated *MEFFreq*, consistent with the argument that earnings projections reveal little useful information to competitors in technological competition.[34] *LLMComp* is also not associated with *MEFFreq*. In contrast, *Fluidity* has a significantly negative coefficient, contrary to its positive association with product disclosure in Equation (4). The contrast between findings in the MEF vs. product disclosure regressions suggests that MEF and product disclosure are distinct types of disclosure and that findings for one may not generalize to the other.

V. SUPPLEMENTARY ANALYSES

Alternative Measures of Product Disclosure

In our primary analysis we measure the amount of product disclosure by a word count. To provide a more complete picture, we now consider alternative measures. *PDFreq* is the number of product-disclosure press releases issued by the firm during fiscal year *t*. Column 1 of Table 10 presents the estimation of a generalized negative binomial model when the dependent variable is *PDFreq,* and the coefficient on *TPP* remains significantly negative.

Our primary measure of product disclosure includes four types of product disclosure information and treats them equally. We now parse each product disclosure press release into the four types and count keyword frequency for each type using the following keywords:

[34] One may predict a positive association between *TPP* and *MEFFreq*. Firms are unlikely to shut down their communication with capital markets but instead choose what to communicate (e.g., financial vs. nonfinancial information, historical vs. forward-looking information, quantitative vs. qualitative information, information about actions vs. outcomes). When facing intense technological competition, a firm may communicate a type of disclosure that has low proprietary content such as MEF. We thank our FARS discussant Mike Minnis for this insight.

(1) R&D Stage: *research, develop, study, deploy, demonstrate, illustrate, test, attempt, aim, experiment*, and their variants.

(2) Product Introduction: *introduce, launch, unveil, release, offer, available, ship, produce, manufacture*, and their variants.

(3) Product Improvement: *improve, enhance, expand, extend, add, strengthen, continue, update*, and their variants.

(4) Product Retirement: *retire, discontinue, cease, stop, phase out, shut off, shut down*, and their variants.

We classify a press release into a category if the document has the highest frequency of keywords for that category. Some press releases (10% of the releases) are assigned to more than one category when there is a tie. Due to the low disclosure frequency of product retirement information, no press releases from our sample firms are classified as product retirement. We create three disclosure variables that correspond to R&D Stage, Product Introduction, and Product Improvement. Each variable is constructed similarly to *Log(PDwords)* except that we count the total words only in the firm's press releases that are classified for the given category. Columns 2–4 of Table 10 report the OLS estimation results when these new disclosure variables are used. *TPP* is negatively associated with all three types of product disclosure, with an economically stronger effect (i.e., the largest magnitude of the coefficient) for R&D Stage disclosure.

Cross-sectional Variation in the Association of *TPP* with Product Disclosure

We explore variation in the association of *TPP* with product disclosure across subsamples partitioned by the technology factor, customer concentration, and a firm's life-cycle stage. The analyses address the concern that our primary finding might result from omitted correlated variables. It would be difficult to argue that omitted variables also result in expected cross-sectional variation.

Given the importance of R&D to high-tech firms, we expect the proprietary costs of disclosure to be higher for these firms and therefore the negative association between *TPP* and product disclosure to be stronger for high-tech firms than for other firms. We follow Bloom et al. (2013) and identify Pharmaceuticals, Computer Hardware, and Telecommunications Equipment firms as high-tech firms.[35] In Columns 1 and 2 of Table 11 we estimate Equation (4) separately for high-tech firms and for other firms. The coefficient for high-tech firms is weakly significantly more negative than that for other firms, consistent with our expectation.

As our interviewees pointed out, one targeted audience of product disclosure is a firm's customers. If a firm generates revenues from only a few major customers, it can simply communicate new product development information privately to these customers. Yet such a strategy is infeasible if the customers are dispersed. In the latter situation, product disclosure can publicly disseminate the product information to dispersed customers. The increased benefits of disclosure will make the proprietary costs of disclosure appear *relatively* smaller and thus weaken the theorized negative relation between *TPP* and product disclosure. We follow Dhaliwal, Judd, Serfling, and Shaikh (2016) and calculate customer concentration using firms' mandatory disclosure of major customers available in Compustat's Segment database. The variable is the sum of the squared proportion of the firm's total sales in fiscal year *t*-1 to each disclosed customer. We classify firm-years with above sample median value of customer concentration as "high" concentration firms. Low customer concentration firms include those without any major customers. Columns 3 and 4 show that the coefficient on *TPP* is indeed significantly less negative for firms with low customer concentration (more dispersed customers).

[35] Pharmaceuticals includes Pharmaceutical Preparations (2834) and In Vitro and In Vivo Diagnostic Substances (2835). Computer Hardware includes Computer and Office Equipment (3570), Electronic Computers (3571), Computer Storage Devices (3572), Computer Terminals (3575), Computer Communications Equipment (3576), and Computer Peripheral Equipment Not Elsewhere Classified (3577). Telecommunications Equipment includes Telephone and Telegraph Apparatus (3661), Radio and TV Broadcasting and Communications Equipment (3663), and Communications Equipment Not Elsewhere Classified (3669).

Guo, Lev, and Zhou (2004) examine product disclosure of 49 biotech IPO firms and find that more disclosure is provided at later stages of product development. The logic is that information disclosure at an early stage of product development may attract rivals who can respond quickly and race ahead of the disclosing firm. Applying the logic to the firm level, we expect that all else being equal, a firm in the early life-cycle stages (e,g., introduction and growth) would incur higher proprietary costs of product disclosure than a firm in the later stages. We follow Dickinson (2011) and classify sample firm-years into five stages of the life cycle: (1) introduction, (2) growth, (3) mature, (4) shakeout, and (5) decline based on firms' cash flow patterns (e.g., the signs of cash flows from operating, investing, and financing activities). The percentage of firm-years classified into the five stages are 13.7%, 24.7%, 38.9%, 11.3%, and 11.3% in sequence. We combine the early stages (stages 1 & 2) and the later stages (stages 3, 4, & 5) separately. Columns 5 and 6 in Table 11 show that as predicted, the association between *TPP* and product disclosure is more negative in the early stages than in the later stages.

Instrumental Variable Estimation

Following Bloom et al. (2013), we use the identification provided by (1) the introduction of state-level R&D tax credits and (2) the enactment of the Uniform Trade Secrets Act. Both events promote R&D activities by firms headquartered in the affected states, introducing exogenous increases to R&D (Png 2017). To understand our instruments, we decompose *TPP* into two components depending on whether a peer firm is headquartered in the same state as the sample firm.

$$TPP_{i,t} \equiv \log\left[1 + \frac{1}{G_{i,t}}\sum\nolimits_{j\neq i} \omega_{ij} \times G_{j,t}\right] = \log\left[1 + \frac{1}{G_{i,t}}\left(\sum\nolimits_{j\neq i} \omega_{ij} \times G_{j,t} \times \mathrm{I}(S_{j,t} \neq S_{i,t}) + \sum\nolimits_{j\neq i} \omega_{ij} \times G_{j,t} \times \mathrm{I}(S_{j,t} = S_{i,t})\right)\right].$$

The first component encapsulates relevant R&D activities conducted by peer firms headquartered outside of the state in which firm i is headquartered. The second component encapsulates relevant

R&D activities conducted by peer firms headquartered in the same state as sample firm i. Here, I (.) is the indicator function and $S_{i,t}$ represents the state in which firm i is headquartered.

Our two instrumental variables (IV) are *TaxCredit* and *UTSA*:

$$TaxCredit_{i,t} \equiv \sum_{j\neq i} \omega_{ij}^{0} \times \mathrm{I}\left(TaxCredit(S_{j,t})\right) \times \mathrm{I}(S_{j,t} \neq S_{i,t})\,;\; UTSA_{i,t} \equiv \sum_{j\neq i} \omega_{ij}^{0} \times UTSA(S_{j,t}) \times \mathrm{I}(S_{j,t} \neq S_{i,t}).$$

In the formulae, $\mathrm{I}\left(TaxCredit(S_{j,t})\right)$ indicates whether at the end of year t the state in which peer firm j is headquartered has introduced tax credit for qualified incremental R&D expenditures; $UTSA(S_{j,t})$ is the state-level index at the end of year t with a higher value representing stronger legal protection of trade secrets; and ω_{ij}^{0} is the closeness of firm j with firm i, calculated using segment sales in 2001 or the year before both firms' first appearance in our sample if they do not enter the sample until after 2002.[36] *TaxCredit* and *UTSA* capture the increases in the R&D stock of the sample firm's *peers* due to the exogenous regulatory changes. These variables are correlated with *TPP* but should not affect the sample firm's product disclosure; therefore, they can serve as instruments for estimating the relation between *TPP* and product disclosure.

We report the IV estimation results in Table 12 using a reduced sample because information for calculating *UTSA* is unavailable after 2008. In Column 1 we replicate our baseline estimation using the reduced sample and find results consistent to our primary analysis. We estimate the two equations of our IV approach in a system with $TaxCredit_{i,t}$ and $UTSA_{i,t}$ being the IVs. As expected, in the first stage the IVs are significantly positively associated with *TPP*. In the second stage, the fitted values of *TPP* are still negatively associated with product disclosure. The identification test shows that the two instruments are highly correlated with *TPP* with the F-

[36] We reconstruct the weight in this way so that it is unlikely to be affected by omitted variables during the same period, ensuring that the instruments satisfy the relevance and exogeneity requirements (Autor, Dorn, and Hanson 2013).

statistic significant at the 1% level and the Cragg–Donald F-statistic greater than the Stock-Yogo critical value of 19.93. The instrument exogeneity test fails to reject the null that the instruments are relevant in the first stage and exogenous in the second stage.

VI. TECHNOLOGICAL PEER PRESSURE VS. TECHNOLOGY SPILLOVER

In this section we differentiate technological peer pressure from technology spillover, a concept that is also examined by Bloom et al. (2013) and is sometimes referred to as "knowledge spillover." The concept is labelled as "R&D spillover" in Jaffe (1986, 984), who states "the existence of technologically related research efforts of other firms may allow a given firm to achieve results with less research effort than otherwise." Thus, technology spillover constitutes a positive externality and enhances a firm's own research ability so that the firm has more resources to withstand competition in its product market. Technology spillover therefore decreases proprietary disclosure costs. So, we expect technology spillover to be positively associated with product disclosure.

As in Jaffe (1986), Bloom et al. (2013) construct a "potential spillover pool" that summarizes the total relevant knowledge (i.e., R&D investments) of other firms, where "relevance" is indicated by the proximity of firm *j* with sample firm *i* in the technology space. The technology space is spanned by 426 classes of patents, which are defined by the US Patent and Trademark Office. We measure technology spillover, *TS,* for firm *i* at the end of year *t* as follows:

$$TS_{i,t} \equiv \log\left[1 + \left(\sum\nolimits_{j \neq i} w_{ij} \times G_{j,t}\right)/TA_{i,t}\right],$$

w_{ij} is the weight in aggregating peer firms' knowledge pool and captures the closeness of firms i and j in the technology space. w_{ij} is calculated as the uncentered correlation of W_i and W_j: $w_{ij} = W_i W_j' / \sqrt{W_i W_i' \times W_j W_j'}$, where W_i is a vector of 426 x 1 with an element being firm i's proportion of the number of patents in the most recent two years in a given patent class. $G_{j,t}$ is peer firm j's R&D stock. TA is firm i's total assets and serves as a scalar. *TS* measures the potential pool of knowledge spillover from firms that use related technology but may not necessarily compete in the same product market. For example, Apple and Microsoft use related technologies, but Apple competes in the computer hardware and personal electronics markets whereas Microsoft competes in computer software.

We obtain patent data from Kogan et al. (2017). That dataset has coverage until 2008, so our number of observations drops to 14,498.[37] Consistent with Bloom et al. (2013) and with the goal of preventing a look-ahead bias, we use the application date, which is about 36 months before the grant date. We decile rank *TS* and *TPP* within this reduced sample. *TS* and *TPP* have a Pearson correlation of -0.161 for this sample, significant at the 5% level.[38] Consistent with the idea that *TPP* captures a negative externality and *TS* captures a positive externality, *TPP* continues to have a negative coefficient whereas the coefficient on *TS* is positive (see Appendix 6). After controlling for *TS*, the coefficient on *TPP* remains significantly negative.

Ettredge, Guo, Lisic, and Tseng (2017) examine the relation between technology spillover and corporate disclosure transparency. They construct three spillover measures: (1) non-directional spillover calculated as the sum of w_{ij}, (2) spill-in calculated as the aggregate R&D of peers in the technology space scaled by property, plant, and equipment (*PPE*), where w_{ij} is the weight for aggregation, and (3) spill-out calculated as the non-directional spillover measure multiplied by the

[37] Compared with the patent database maintained by the National Bureau of Economic Research that ends in 2006, the new patent data constructed by Kogan et al. (2017) have more coverage. For instance, this database adds on average more than 2,000 patents per year and provides a matched Permco (ID in CRSP) for 66% of all patents with an assignee compared with a percentage of 32% for NBER's patent database.

[38] One caveat of our *TS* measure is that we retain the 7,443 firm-years that have positive R&D stock but no patents and assign the value of 0 to *TS*. If we remove these observations, the correlation between *TPP* and *TS* decile-ranked variables is 0.556 and *TPP* (*TS*) remains to have a negative (positive) coefficient in the product disclosure regression.

ratio of G_i to PPE_i. In untabulated analysis, we calculate the spill-in and spill-out measures (without adding 1 in the logarithm to be consistent with Ettredge et al.) for 7,055 firm-years with available data and find both spill-in and spill-out are positively associated with product disclosure.

As Bloom et al. (2013) point out, technology spillover is a positive externality; in contrast, product market rivalry, which is what we use to develop our *TPP* measure, captures the business stealing effect and is thus a negative externality. Technology spillover and technological peer pressure are conceptually different but empirically correlated. Future research may further explore the implications of these two concepts for corporate reporting and disclosure decisions.

VII. CONCLUSION

Competition and disclosure are multidimensional. Theories of the relation between competition and disclosure assume only one dimension of each within a model and generally demonstrate a negative relation. Empirical examinations of this relation have yielded mixed evidence perhaps due to multidimensionality. One should not expect to find a negative association between any pair of competition and disclosure measures. We call researchers' attention to the multidimensionality of competition and disclosure by (1) introducing a new dimension of competition—technological competition, (2) examining an overlooked type of disclosure—product disclosure, and (3) providing evidence that the theorized negative relation between competition and disclosure exists only when the dimension of competition and the type of disclosure are aligned.

References

Aizcorbe, A. 2005. Moore's law, competition, and Intel's productivity in the mid-1990s. *The American Economic Review* 95 (2): 305-308.

Ajinkya, B., S. Bhojraj, and P. Sengupta. 2005. The association between outside directors, institutional investors and the properties of management earnings forecasts. *Journal of Accounting Research* 43 (3): 343-376.

Ali, A., S. Klasa, and E. Yeung. 2014. Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics* 58 (2–3): 240-264.

Asker, J. and A. Ljungqvist. 2010. Competition and the structure of vertical relationships in capital markets. *Journal of Political Economy* 118 (3): 599-647.

Autor, D. H., D. Dorn, and G. H. Hanson. 2013. The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review* 103 (6): 2121–2168.

Bamber, L. S. and Y. S. Cheon. 1998. Discretionary management earnings forecast disclosures: Antecedents and outcomes associated with forecast venue and forecast specificity choices. *Journal of Accounting Research* 36 (2):167-190.

Bertrand, J. L. F. 1883. Book review of theorie mathematique de la richesse sociale and of recherches sur les principles mathematiques de la theorie des richesses. *Journal de Savants* 67: 499–508.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther. 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics* 50 (2-3): 296-343.

Bloom, N., M. Schankerman, and J. Van Reenen. 2013. Identifying technology spillovers and product market rivalry. *Econometrica* 81 (4): 1347-1393.

Bonsall, S. B, A. J. Leone, B. P. Miller, and K. Rennekamp. 2016. A plain English measure of financial reporting readability. Working paper.

Cantner, U., J.-L. Gaffard, and L. Nesta, eds. 2009. *Schumpeterian perspectives on innovation, competition and growth*. Dordrecht, NY: Springer.

Chartered Institute of Marketing. 2009. *How to get to grips with your competitors*. Berkshire, UK.

Cournot, A. A. 1838. *Recherches sur les principes mathématiques de la théorie des richesses*. L. Hachette.

Cummings, J. L., T. Morstorf, and K. Zhong. 2014. Alzheimer's disease drug-development pipeline: Few candidates, frequent failures. *Alzheimer's research & therapy* 6 (4): 37-37.

Dhaliwal, D., J. S. Judd, M. Serfling, and S. Shaikh. 2016. Customer concentration risk and the cost of equity capital. *Journal of Accounting and Economics* 61: 23-48.

Darrough, M. N. 1993. Disclosure policy and competition Cournot vs. Bertrand. *Accounting Review* 68 (3): 534-561.

Darrough, M. N. and N. M. Stoughton. 1990. Financial disclosure policy in an entry game. *Journal of Accounting and Economics* 12 (1): 219-243.

Dedman, E. and C. Lennox. 2009. Perceived competition, profitability and the withholding of information about sales and the cost of sales. *Journal of Accounting and Economics* 48 (2–3): 210-230.

Dickinson, V. 2011. Cash Flow Patterns as a Proxy for Firm Life Cycle. *The Accounting Review* 86 (6): 1969-1994.

Dixit, A. K. and J. E. Stiglitz. 1977. Monopolistic competition and optimum product diversity. *The American Economic Review* 67 (3): 297-308.

Dye, R. A. 2001. An evaluation of "essays on disclosure" and the disclosure literature in accounting. *Journal of Accounting and Economics* 32 (1–3): 181-235.

Eisdorfer, A. and P. Hsu. 2011. Innovate to survive: The effect of technology competition on corporate bankruptcy. *Financial Management* 40 (4): 1087-1117.

Ettredge, M., F. Guo, L. L. Lisic, and K. Tseng. 2017. Technology spillover and corporate disclosure transparency. Working paper, University of Kansas. July.

Frankel, R., M. McNichols, and G. P. Wilson. 1995. Discretionary disclosure and external financing. *Accounting Review* 70 (1):135-150.

Farrell, A. M, J. H. Grenier, and J. Leiby. 2017. Scoundrels or stars? Theory and evidence on the quality of workers in online labor markets. *The Accounting Review* 92 (1): 93-114.
Futia, C. A. 1980. Schumpeterian competition. *The Quarterly Journal of Economics* 94 (4): 675-695.
Galor, O. and D. N. Weil. 2000. Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond. *The American Economic Review* 90 (4):806-828.
Gersbach, H. and A. Schmutzler. 2012. Product markets and industry-specific training. *The RAND Journal of Economics* 43 (3): 475-491.
Gigler, F. 1994. Self-enforcing voluntary disclosures. *Journal of Accounting Research* 32 (2): 224-240.
Grossman, S. J. 1981. The informational role of warranties and private disclosure about product quality. *The Journal of Law & Economics* 24 (3): 461-483.
Grove, A. S. 1996. Only the paranoid survive: How to exploit the crisis points that challenge every company and career. New York, NY: Currency Doubleday.
Guo, R., B. Lev, and N. Zhou. 2004. Competitive costs of disclosure by biotech IPOs. *Journal of Accounting Research* 42 (2): 319-355.
Hayes, R. M. and R. Lundholm. 1996. Segment reporting to the capital market in the presence of a competitor. *Journal of Accounting Research* 34 (2): 261-279.
Helm, B. 2011. How to use competitive intelligence to gain an advantage. *Inc.*
Hoberg, G., G. Phillips, and N. Prabhala. 2014. Product market threats, payouts, and financial flexibility. *The Journal of Finance* 69 (1): 293-324.
Hotelling, H. 1929. Stability in competition. *The Economic Journal* 39 (153): 41-57.
Houston, J. F., B. Lev, and J. W. Tucker. 2010. To guide or not to guide? Causes and consequences of stopping quarterly earnings guidance. *Contemporary Accounting Research* 27 (1): 143-185.
Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review* 76 (5): 984-1001.
Jin, G. Z. 2005. Competition and disclosure incentives: An empirical study of HMOs. *The RAND Journal of Economics* 36 (1): 93-112.
Jovanovic, B. 1982. Truthful disclosure of information. *The Bell Journal of Economics* 13 (1): 36-44.
Kogan, L, D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* 132 (2): 665-712.
Koh, P.-S. and D. M. Reeb. 2015. Missing R&D. *Journal of Accounting and Economics* 60 (1): 73-94.
Koten, J. 2013. Manufacturing: Unleashing innovation (a special report) --- A revolution in the making: Digital technology is transforming manufacturing, making it leaner and smarter, and raising the prospect of an American industrial renaissance. *The Wall Street Journal*.
Kwiatkowski, D., P. Phillips, P. Schmidt, and Y. Shin. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics* 54 (1): 159-178.
Lang, M. and E. Sul. 2014. Linking industry concentration to proprietary costs and disclosure: Challenges and opportunities. *Journal of Accounting and Economics* 58 (2–3): 265-274.
Levin, A., C. Lin, and C. J. Chu. 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics* 108: 1-24.
Li, F., R. Lundholm, and M. Minnis. 2013. A measure of competition based on 10-K filings. *Journal of Accounting Research* 51 (2): 399-436.
Li, X. 2010. The impacts of product market competition on the quantity and quality of voluntary disclosures. *Review of Accounting Studies* 15 (3): 663-711.
Lu, H. and J. W. Tucker. 2012. Nonearnings corporate guidance. *Financial Management* 41 (4): 947-977.
Ma, G. 2012. Stock market response to voluntary operations-related disclosures. Working paper, National University of Singapore.
Merkley, K. J. 2014. Narrative disclosure and earnings performance: Evidence from R&D disclosures. *The Accounting Review* 89 (2): 725-757.
Miller, G. S. 2002. Earnings performance and discretionary disclosure. *Journal of Accounting Research* 40 (1): 173-204.

National Science Foundation. 1998. *High-tech industries drive global economic activity*. Division of Science Resources Studies. Issue Brief, NSF 98-319.
Peterson, K. and N. Tran. 2014. Managers' discussion of competition in the 10-K, firms' investing activities and future operating performance. Working paper, University of Oregon.
Png, I. P. L. 2017. Law and innovation: Evidence from state trade secrets laws. *Review of Economics and Statistics* 99: 167-179.
Qiu, J. and C. Wan. 2015. Technology spillovers and corporate cash holdings. *Journal of Financial Economics* 115 (3): 558-573.
Raith, M. 2003. Competition, risk, and managerial incentives. *American Economic Review* 93 (4): 1425-1436.
Schumpeter, J. A. 1934. *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Vol. 46. Cambridge, MA: Harvard University Press.
———. 1957. *Capitalism, socialism, and democracy*. Vol. 4th. London: Allen and Unwin.
Severinov, S. 2001. On information sharing and incentives in R&D. *The RAND Journal of Economics* 32 (3): 542-564.
Sharp, S. 2009. *Competitive intelligence advantage: How to minimize risk, avoid surprises, and grow your business in a changing world*. Hoboken, NJ: John Wiley & Sons.
Solow, R. M. 1956. A contribution to the theory of economic growth. *The Quarterly Journal of Economics* 70 (1): 65-94.
———. 1957. Technical change and the aggregate production function. *The Review of Economics and Statistics* 39 (3): 312-320.
Stahl, D. O. 1988. Bertrand competition for inputs and Walrasian outcomes. *The American Economic Review* 78 (1): 189-201.
Stigler, G. J. 1963. Competition and the rate of return. In *Capital and rates of return in manufacturing industries*. Princeton, NY: Princeton University Press, 54 - 71.
Thaler, R. H. 2015. *Misbehaving: The making of behavioral economics*. New York, NY: Norton.
Verrecchia, R. E. 1983. Discretionary disclosure. *Journal of Accounting and Economics* 5 (C): 179-194.
Verrecchia, R. E. 2001. Essays on disclosure. *Journal of Accounting and Economics* 32 (1–3): 97-180.
Verrecchia, R. E. and J. Weber. 2006. Redacted disclosure. *Journal of Accounting Research* 44 (4): 791-814.
Vives, X. 1989. Technological competition, uncertainty, and oligopoly. *Journal of Economic Theory* 48 (2): 386-415.
Wagenhofer, A. 1990. Voluntary disclosure with a strategic opponent. *Journal of Accounting and Economics* 12 (4): 341-363.
Waymire, G. 1985. Earnings volatility and voluntary management forecast disclosure. *Journal of Accounting Research* 23 (1): 268-295.
Weeds, H. 2002. Strategic delay in a real options model of R&D competition. *Review of Economic Studies* 69 (3): 729-747.
Wersching, K. 2010. Schumpeterian competition, technological regimes and learning through knowledge spillover. *Journal of Economic Behavior & Organization* 75 (3): 482-493.
Zingales, L. 2000. In search of new foundations. *The Journal of Finance* 55 (4):1623-1653.

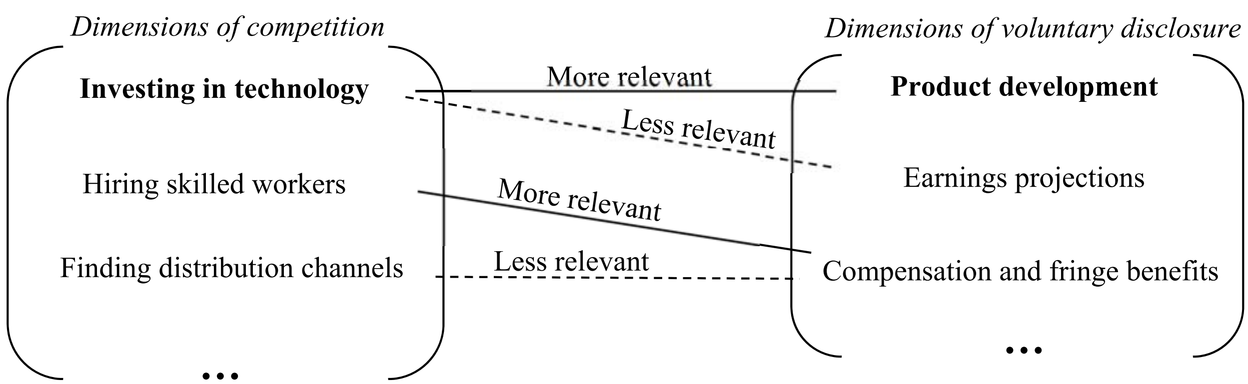
APPENDIX 1
Framework

Product-market competition ——————————— Capital-market disclosure

Proprietary disclosure costs
(Three elements)

1. Alignment

- Alignment means that information revealed in the type of disclosure is relevant to rivals within the specific dimension of competition.
- If there is no alignment, then there are no proprietary disclosure costs.



2. Intensity of competition

- The more intense the competition, the more damage a given piece of proprietary information can inflict on the disclosing firm through its rivals' actions and therefore the higher the *proprietary disclosure costs*.
- We use *TPP* to measure the intensity of technological competition.

3. Amount of disclosure

- The greater the amount of disclosure, the more proprietary information is revealed and therefore the higher the *proprietary costs*.
- We use the total number of words in a firm-year's product-disclosure press releases to measure the amount of disclosure.

Empirical Prediction

The intensity of competition is negatively associated with the amount of subsequent disclosure only when the type of disclosure is aligned with the dimension of competition under examination; otherwise, the theorized negative relation may not be observed.

APPENDIX 2
Technological Peer Pressure

Panel A: Mean value of technological peer pressure (*TPP*) with the number of observations for independently double-sorted portfolios presented below *TPP*

	Sorting by the denominator of *TPP*—a firm's own R&D stock									
Sorting by the numerator of *TPP*—pool of peers' R&D stock	1 (lowest)	2	3	4	5	6	7	8	9	10 (highest)
1 (lowest)	0.964	0.166	0.052	0.041	0.003	0.006	0.005	0.003	0.000	0.000
	338	213	226	203	153	157	178	171	179	203
2	5.54	3.27	2.39	1.77	1.54	1.16	0.77	0.60	0.40	0.13
	558	306	275	205	160	133	161	110	63	50
3	7.34	5.09	4.21	3.60	3.06	2.60	2.19	1.65	1.13	0.55
	331	333	227	206	206	196	144	142	170	66
4	8.35	6.08	5.18	4.53	4.01	3.50	3.14	2.67	1.92	0.89
	285	250	227	183	175	203	143	176	193	185
5	8.84	6.98	6.03	5.35	4.81	4.31	3.86	3.33	2.58	1.32
	229	264	190	217	154	188	175	162	214	228
6	8.97	7.26	6.28	5.69	5.17	4.58	4.19	3.70	2.90	1.48
	66	186	220	249	263	156	224	184	228	245
7	9.36	7.59	6.76	6.03	5.56	5.08	4.57	4.07	3.31	1.55
	90	178	196	210	236	194	239	202	188	287
8	9.56	8.04	7.29	6.68	6.13	5.62	5.19	4.71	4.00	2.04
	36	131	178	144	206	249	245	300	261	271
9	10.18	8.84	7.96	7.37	6.80	6.31	5.85	5.35	4.60	2.63
	46	88	155	242	328	324	261	259	178	140
10 (highest)	10.21	9.09	8.27	7.61	7.01	6.55	6.11	5.59	4.75	2.82
	42	72	127	161	140	221	250	315	347	345

Panel B: Distribution of technological peer pressure (*TPP*) by major industries

4-digit SIC	Industry	N	Mean	Median	Std. Dev.
7372	Prepackaged software	1,780	6.070	6.204	1.605
2834	Pharmaceutical preparations	1,396	5.367	5.830	2.612
3674	Semiconductors and related devices	1,226	5.609	5.775	1.745
2836	Biological products, except diagnostic substances	979	4.364	4.812	2.049
7370	Computer programming, data processing, and other	623	4.855	5.050	2.166
3845	Electro-medical and electrotherapeutic apparatus	556	5.077	5.393	2.070
7373	Computer integrated systems design	523	5.453	5.609	2.127
3663	Broadcasting and communications equipment	479	5.385	5.621	1.997
2835	In Vitro and In Vivo diagnostic substances	350	4.373	4.596	2.006
3841	Surgical and medical instruments and apparatus	332	5.203	5.539	1.920
3842	Orthopedic, prosthetic, and surgical appliances	325	5.151	5.183	2.076
3559	Special industry machinery	312	4.367	4.233	2.115
3661	Telephone and telegraph apparatus	284	4.712	4.613	1.876
3576	Computer communications equipment	280	4.440	4.504	1.543
3679	Electronic components	264	5.200	4.603	2.543
3714	Motor vehicle parts and accessories	236	4.853	5.202	2.373
3826	Laboratory analytical instruments	224	3.679	3.587	1.683
3690	Miscellaneous electrical machinery, equipment, and supplies	214	3.629	3.223	2.053
3577	Computer peripheral equipment	207	4.669	5.162	1.895
3825	Instruments for electricity and electrical signals	204	4.064	4.313	1.662
	Subtotal	10,794	4.826	4.953	2.006
	Other industries	9,413	2.891	2.700	1.622
	Total	20,207			

Panel C: Distribution of technological peer pressure (*TPP*) by year

Year	N	Mean	Median	Std. Dev.	Mean of industry Std. Dev.	Std. Dev. of industry mean
2002	2,306	4.602	4.886	2.480	2.247	1.961
2003	2,217	4.483	4.766	2.472	2.189	1.918
2004	2,190	4.452	4.669	2.495	2.184	1.929
2005	2,096	4.388	4.633	2.505	2.136	1.893
2006	2,048	4.251	4.517	2.542	2.069	1.889
2007	1,951	4.262	4.547	2.538	2.076	1.988
2008	1,916	4.186	4.453	2.552	2.037	1.994
2009	1,903	4.159	4.396	2.527	2.056	1.863
2010	1,821	4.052	4.288	2.527	1.980	1.923
2011	1,759	4.004	4.201	2.537	1.897	1.961
Total	20,207					

Panel D: Transition matrix of technological peer pressure (*TPP*) in deciles

Percentage	*TPP* $_t$									
TPP $_{t-1}$	1 (lowest)	2	3	4	5	6	7	8	9	10 (highest)
1 (lowest)	85.7	7.6	0.9	0.7	0.9	0.8	0.9	1.3	0.7	0.5
2	4.4	84.8	9.9	0.5	0.2	0.0	0.1	0.1	0.1	0.1
3	1.3	5.4	80.9	11.5	0.6	0.2	0.0	0.1	0.0	0.0
4	1.2	0.5	6.9	78.2	12.4	0.6	0.2	0.0	0.1	0.0
5	1.1	0.4	0.1	7.6	76.5	13.4	0.6	0.3	0.1	0.0
6	0.5	0.2	0.2	0.7	8.3	76.3	13.0	0.7	0.2	0.1
7	1.1	0.0	0.2	0.2	0.5	8.8	75.6	12.9	0.5	0.2
8	1.2	0.0	0.1	0.2	0.3	0.9	10.0	77.1	10.3	0.0
9	1.2	0.1	0.3	0.2	0.1	0.2	0.2	8.4	83.4	6.1
10 (highest)	1.0	0.1	0.1	0.1	0.1	0.1	0.0	0.5	6.9	91.2

Note: See the definition of *TPP* in Appendix 5. In Panel A, we loosely refer to the pool of peers' R&D stock as the numerator and a firm's R&D stock as the denominator, ignoring the number of 1 and the log transformation of the ratio. The precise sorting is by the log transformation of 1 plus the numerator and by the log transformation of 1 plus the denominator. In Panel B, we present the mean, median, and standard deviation of *TPP* for each of the 20 largest industries. The numbers at the bottom of the table for the 20 industries as a whole and for the other industries are calculated first for each industry in the group and then averaged across industries within that group. In Panel C, we present the mean, median, and standard deviation of *TPP* for each sample year. We add the mean value of the standard deviation of *TPP* within a 4-digit SIC code to show the variation of *TPP within* an industry. We add the standard deviation of the mean of *TPP* for each industry to show the variation of *TPP across* industries. In Panel D, we present the percentage of firms in a given decile of *TPP* in year *t*-1 that belong to a particular decile of *TPP* in year *t*.

APPENDIX 3
Example of Product Disclosure

IBM Watson Health Announces Collaboration to Study the Use of Blockchain Technology for Secure Exchange of Healthcare Data

ARMONK, N.Y., Jan. 11, 2017 /PRNewswire/ -- IBM Watson Health (NYSE: IBM) has signed a research initiative with the U.S. Food and Drug Administration (FDA) aimed at defining a secure, efficient and scalable exchange of health data using blockchain technology. IBM and the FDA will explore the exchange of owner mediated data from several sources, such as Electronic Medical Records, clinical trials, genomic data, and health data from mobile devices, wearables and the "Internet of Things." The initial focus will be on oncology-related data.

Transformative healthcare solutions are possible when healthcare researchers and providers have access to a 360-degree view of patient data. Today, patients have little access to their health data and cannot easily share with researchers or providers. Giving patients the opportunity to share their data securely, for research purposes or across their healthcare providers, creates opportunities for major advancements in healthcare. Blockchain technology, which enables organizations to work together with more trust, is designed to help make this a reality.

By keeping an audit trail of all transactions on an unalterable distributed ledger, blockchain technology establishes accountability and transparency in the data exchange process. In the past, large scale sharing of health data has been limited by concerns of data security and breaches of patient privacy during the data exchange process.

A recent IBM Institute for Business Value paper 'Healthcare rallies for blockchains', based on a survey of about 200 healthcare executives, found that more than seven in ten industry leaders anticipate the highest benefits of blockchain in healthcare to accrue to managing clinical trial records, regulatory compliance and medical/health records.

IBM and the FDA will explore how a blockchain framework can potentially provide benefits to public health by supporting important use cases for information exchange across a wide variety of data types, including clinical trials and "real world" evidence data. New insights combining data across the healthcare ecosystem can potentially lead to new biomedical discoveries. Patient data from wearables and connected devices for example, can help doctors and caregivers better manage population health.

The collaboration will also address new ways to leverage the large volumes of diverse data in today's biomedical and healthcare industries. A secure owner-mediated data sharing ecosystem could potentially hold the promise of new discoveries and improved public health.

IBM brings extensive expertise in blockchain technology, for example, IBM is founding member and key contributor to the Linux Foundation's Hyperledger project.
As the promise of blockchain in healthcare becomes increasingly evident, IBM will work to define and build the technological solution for a scalable and decentralized data sharing ecosystem.

"The healthcare industry is undergoing significant changes due to the vast amounts of disparate data being generated. Blockchain technology provides a highly secure, decentralized framework for data sharing that will accelerate innovation throughout the industry," said Shahram Ebadollahi, Vice President for Innovations and Chief Science Officer, IBM Watson Health.

The initiative with the FDA is a two-year agreement. IBM Watson Health and the FDA plan to share initial research findings in 2017.

APPENDIX 4

Are Product Disclosure Press Releases Perceived to Contain Proprietary Information?

Full-sample analysis	N	Mean	Std. Dev.	*t*-statistic	
Score $_{PD}$	188	2.383	1.896		
Score $_{MEF}$	188	1.814	1.924		
Score $_{PD\text{-}MEF}$	188	0.569	2.374	3.20***	
Subsample analysis					
Education	No degree	High school	2-year college	4-year college	Graduate
N	0	39	27	86	36
Score $_{PD\text{-}MEF}$		0.641*	-0.259	0.605***	1.028**
Working in computer/tech	None	Less than 5 years	5 - 10 years	More than 10 years	
N	66	64	26	32	
Score $_{PD\text{-}MEF}$	0.833***	0.297	0.038	0.416**	
Managerial experience	None	Less than 5 years	5 - 10 years	More than 10 years	
N	78	73	26	11	
Score $_{PD\text{-}MEF}$	0.705***	0.315	1.077***	0.091	
Employment	Full-time	Part-time	Self-employed	Not working	
N	118	14	33	23	
Score $_{PD\text{-}MEF}$	0.653***	1.143*	0.394	0.043	
Age	Less than 20	20 - 39	40 - 59	60 -70	
N	2	121	58	7	
Score $_{PD\text{-}MEF}$	0.500	0.471**	0.793***	0.429	
Gender	Male	Female			
N	112	76			
Score $_{PD\text{-}MEF}$	0.643**	0.461**			

Note: We hired 206 participants on Amazon Mechanical Turk after screening them for financial literacy and computer/technology knowledge. Eighteen responses failed the validity check. We gave each participant a product-disclosure (PD) press release and an MEF press release with the order of the presentation being random. The product disclosure was randomly selected from three documents; the MEF was also randomly selected from three documents. The six documents are real press releases issued by computer/technology related companies in the first 60 days of 2017. We replace company names with fake names (e.g., Omega, Zeta, Lamda, Alpha, Gamma, and Theta). Each participant answered four questions after reading the assigned document: (1) To what extent does the press release contain proprietary information that the company would not want its competitors to know? (2) To what extent could the press release damage the company's competitive advantage (i.e., the company's competitors may take actions based on the information and these actions may hurt the company's market share or profitability)? (3) How difficult did you find this evaluation task to be? and (4) What is this press release about? The first two questions ask the same thing in different ways; the answers are recorded as 0 for "not at all," 1 for "a little," 2 for "some," 3 for "a fair amount," and 4 for "a lot." *Score* $_{PD}$ (*Score* $_{MEF}$) is the sum of answers to both questions. *Score* $_{PD\text{-}MEF}$ is *Score* $_{PD}$ minus *Score* $_{MEF}$. The fourth question is a validation check. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX 5
Variable Definitions

Technological peer pressure for firm *i* at the end of fiscal year *t*:

TPP = $\log\left[1 + \left(\sum_{j \neq i} \omega_{ij} \times G_{j,t}\right) / G_{i,t}\right]$, where *j* represents firm *i*'s rival (any firm that overlaps with firm *i* in the product markets), *t* represents the fiscal year, *G* is a firm's R&D stock, and ω_{ij} is the closeness weight. Specifically, *G* is a firm's cumulative R&D investments in preceding years with the value of investments decaying by 15% as each year passes, i.e., $G_t = R\&D_t + (1\text{-}15\%)G_{t-1}$, where $R\&D_t$ is the firm's R&D expenses in year *t*. ω_{ij} captures the spatial distance in the product markets between firms *i* and *j* using industry segment sales:
$\omega_{ij} \equiv \cos(\theta_{ij}) = \langle \frac{V_i}{\|V_i\|} \cdot \frac{V_j}{\|V_j\|} \rangle$, where V_i is the vector of firm i's sales with the k^{th} element being the share of firm i's total sales in the preceding two years made in industry (4-digit SIC) k. A higher value of *TPP* indicates more intense competition faced by the sample firm.

Other firm-specific measures of product-market competition for firm *i* at the end of fiscal year *t*:

LLMComp = the measure of competition introduced by Li et al. (2013). We calculate *LLMComp* for our sample firms following the procedures for *PCTCOMP* in Li et al. *LLMComp* is the number of competition-related words in the firm's 10-K report divided by the total number of words in the report, expressed as one per 1,000. A higher value of *LLMComp* indicates more intense competition faced by the sample firm.

Fluidity = the measure of product-market threat introduced by Hoberg, Phillips, and Prabhala (2014). *Fluidity* measures the extent to which the words used by the sample firm in its Item 1 "business descriptions" of the 10-K report are adopted or dropped by other firms. We obtain this measure from the website of http://hobergphillips.usc.edu/industryconcen.htm. Hoberg et al. interpret a higher value of *Fluidity* as a more intense competitive threat faced by the sample firm.

Product disclosure by firm *i* during fiscal year *t:*

PDwords = the total number of words (including numbers) in all product-development-related press releases issued by the firm during fiscal year *t*. We identify disclosure events related to product development, introduction, improvement, or retirement in Capital IQ's Key Development Database and obtain the press releases from Thomson Reuters' News Analytics Database. Common stop words are excluded from the word count.

Other voluntary disclosure measures used in prior research for fiscal year *t* of firm *i*:

Merkley = the measure of narrative R&D disclosure introduced by Merkley (2014). We calculate *Merkley* for our sample firms following the procedures for $R\&D\ DISC_{QTY}$ in Merkley (2014). Simply put, *Merkley* is the total number of R&D-related sentences in the sample firm's 10-K report.

MEFFreq = the number of management forecasts for fiscal year *t*'s earnings issued by the firm during fiscal year *t* according to IBES's Earnings Guidance database.

Alternative variables of product disclosure:	
PDFreq	= the number of the firm's product disclosure press releases issued during fiscal year *t*.
PDwords (R&D stage)	= the total number of words in the firm's press releases issued during fiscal year *t* that are classified as related to R&D activity.
PDwords (Product intro.)	= the total number of words in the firm's press releases issued during fiscal year *t* that are classified as related to product introduction.
PDwords (Product impro.)	= the total number of words in the firm's press releases issued during fiscal year *t* that are classified as related to product improvement.
Control variables defined for fiscal year *t* of firm *i*. We use lagged control variables in regressions*:*	
PDdum	= 1 if the firm provides any product disclosure press release during fiscal year *t* and 0 otherwise.
Merkdum	= 1 if the firm provides any R&D disclosure in the 10-K report for fiscal year *t* and 0 otherwise.
MEFdum	= 1 if the firm issues any forecasts for annual earnings during fiscal year *t* and 0 otherwise.
MVE	= the market value of equity at the end of fiscal year *t* (Compustat).
StdRet	= the stock return volatility during fiscal year *t* using monthly returns (CRSP).
Analysts	= the number of financial analysts whose forecasts of the firm's annual earnings are included in the last consensus before the end of fiscal year *t* (IBES Summary).
IO	= the percentage of shares owned by institutional investors at the end of fiscal year *t* (Thomson-Reuters' Institutional Holdings 13F Database).
M/B	= the ratio of market value of equity to book value of equity at the end of fiscal year *t* (Compustat).
Leverage	= the sum of long-term debt and the current portion of long-term debt scaled by total assets, all measured at the end of fiscal year *t* (Compustat).
StdEarn	= the standard deviation of earnings before extraordinary items and discontinued operations scaled by total assets in fiscal years *t-4* to *t* with a minimum requirement of three observations (Compustat).
ΔEPS	= the change in earnings per share from fiscal year *t-1* to *t,* scaled by the stock price at the end of fiscal year *t* (Compustat).
ISSUE	= 1 if the firm issues equity in fiscal years *t+2* to *t+3* (skipping year *t*+1) and 0 otherwise (SDC). The variable measures equity financing anticipated by managers at the end of fiscal year *t*. For each year we calculate the equity issuance size as the proceeds scaled by total assets at the beginning the fiscal year and count the total equity issuance size that is at least 3% to exclude small issuances (e.g., issuances for employee stock options exercises).

APPENDIX 6
Technological Peer Pressure vs. Technology Spillover

Y = log (1+PDwords$_t$)	(1)	(2)	(3)
TPP$_{t-1}$	-0.542***		-0.387***
	(-4.15)		(-3.00)
TS$_{t-1}$		1.145***	1.126***
		(15.10)	(14.89)
PDdum$_{t-1}$	1.723***	1.704***	1.685***
	(17.46)	(17.69)	(17.35)
Other controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adjusted R^2	47.7%	48.9%	48.9%
N	14,498	14,498	14,498

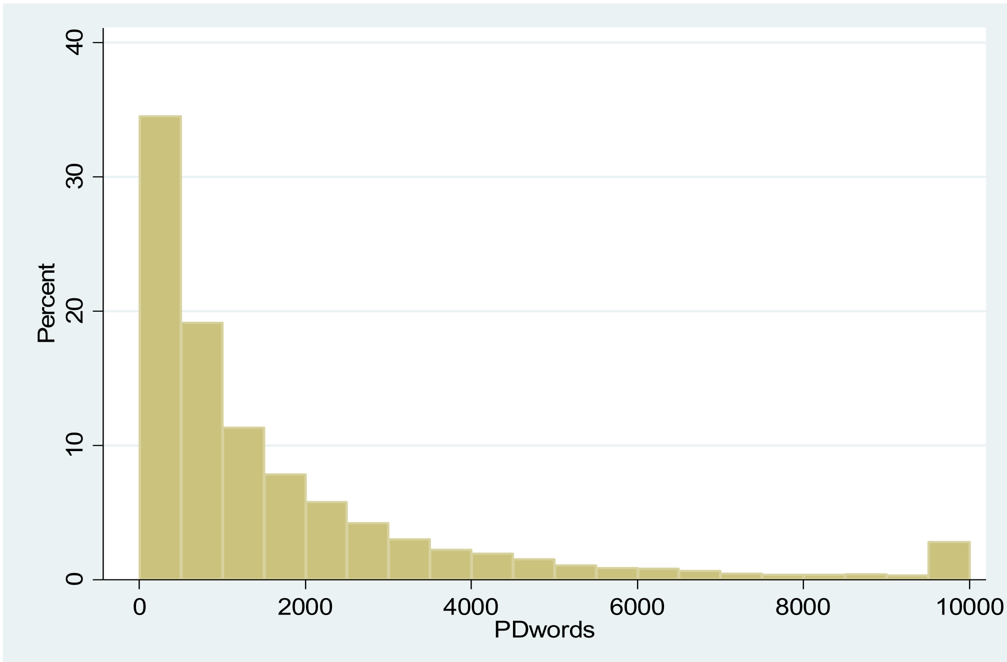
Note: We calculate the technology spillover, *TS*, for firm *i* at the end of year *t* as follows:

$$TS_{i,t} \equiv \log\left[1 + \left(\sum\nolimits_{j \neq i} w_{ij} \times G_{j,t}\right)/TA_{i,t}\right],$$

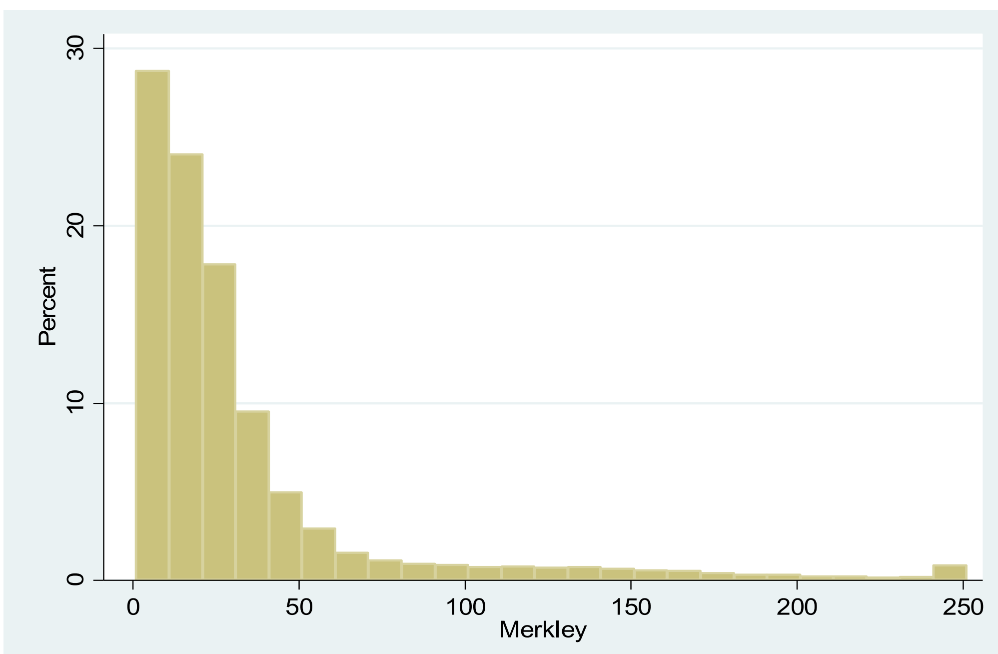
In this formula, w_{ij} is the weight used in aggregating peer firms' knowledge pool, $G_{j,t}$ is peer firm *j*'s R&D stock, and *TA* is firm *i*'s total assets serving as a scalar. Different from the weights in the *TPP* measure, here Specifically, w_{ij} captures the closeness of firms i and j in the technology space and is calculated as the uncentered correlation of W_i and W_j : $w_{ij} = W_i W_j' / \sqrt{W_i W_i' \times W_j W_j'}$, where W_i is a vector of 426 x 1 with an element being firm i's proportion of the number of patents in the most recent two years in a given patent class (426 classes in total) of the US Patent and Trademark Office. Because of patent data availability until 2008, our sample is reduced to 14,498 firm-years. We decile-rank *TPP* and *TS* within this reduced sample with the ranked values ranging from 0 to 1. We report the OLS estimations with *t*-statistics in parentheses and standard errors robust to heteroskedasticity and clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

FIGURE 1
Distribution of Voluntary Disclosure Measures

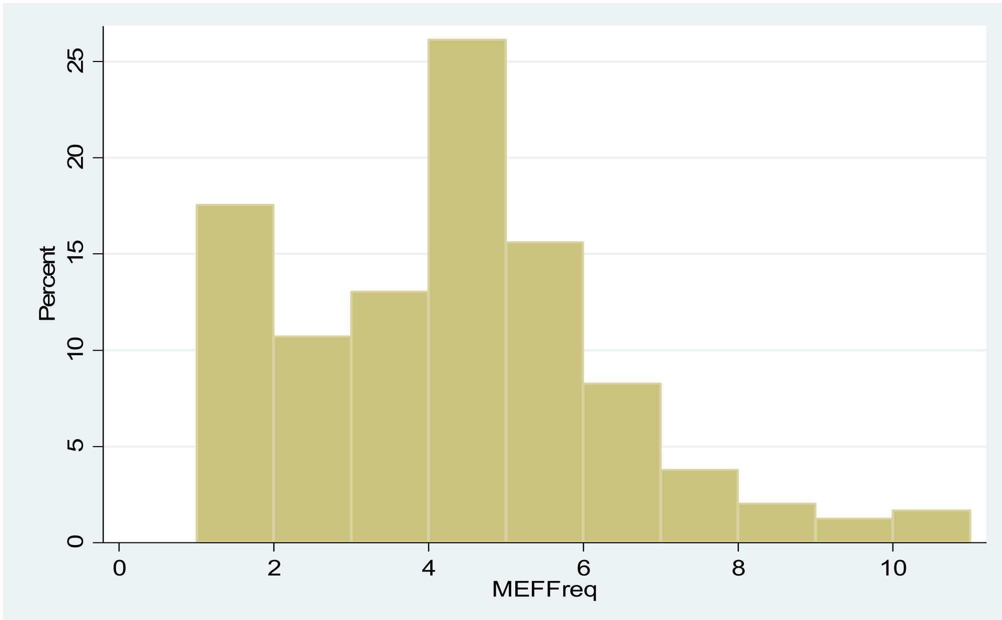
Panel A: Histogram of a firm's total word count of product disclosure for disclosing firm-years



Panel B: Histogram of a firm's total number of R&D related sentences in the 10-K report for disclosing firm-years



Panel C: Histogram of a firm's number of management earnings forecasts for disclosing firm-years



Note: Panel A plots the distribution of *PDwords*, a firm-year's total word count of product disclosure, for the firms that provide such disclosure (59.7% of the 20,207 sample firm-years). The width of a bar is 500 words. Panel B plots the distribution of *Merkley*, a firm-year's total number of R&D related sentences in its 10-K report, for the firms that provide such disclosure (80.6% of the 20,207 sample firm-years). Panel C plots the distribution of *MEFFreq*, defined as a firm-year's number of management earnings forecasts, for the firms that provide such disclosure (24.3% of the 20,207 sample firm-years). The first bar represents the percentage of the firms that provide exactly one forecast during the year. The tallest bar represents the percentage of the firms that provide a total of four forecasts during the year. The last bar of the three panels represents the percentage of disclosing firms that provide more than 9,000 *PDwords*, more than 240 R&D sentences in the 10-K, and more than 10 *MEF*.

TABLE 1
Sample Selection

	Attrition	Remaining observations
Firm-years in North America Compustat for fiscal years 2002–2012		42,710
Exclude financial services and utilities companies	(1,685)	41,025
Exclude firm-years without data for control variables, which are measured at the end of the previous year.	(7,306)	33,719
Exclude firm-years with zero R&D stock	(13,512)	20,207
Test sample during 2003–2012		20,207

TABLE 2
Competition and Disclosure—Descriptive Statistics

Panel A: Descriptive statistics of sample firm-year observations

	N	Mean	Median	Std. Dev.
Firm-specific competition measures				
TPP_{t-1}	20,207	4.299	4.552	2.522
$LLMComp_{t-1}$	16,861	1.190	1.108	0.581
$Fluidity_{t-1}$	17,029	7.542	7.095	3.504
Voluntary disclosure measures				
$PDwords_t$	20,207	1,142.2	152	2,750.2
$Merkley_t$	20,207	26.3	14	40.7
$MEFFreq_t$	20,207	0.9	0	1.9
Alternative measures of product disclosure				
$PDFreq_t$	20,207	4.6	1	12.0
$PDwords_t$ *(R&D stage)*	20,207	447.0	0	1,191.3
$PDwords_t$ *(Product intro.)*	20,207	563.7	0	1,721.1
$PDwords_t$ *(Product impro.)*	20,207	269.4	0	842.3
Control variables				
$PDdum_{t-1}$	20,207	0.597	1	N/A
$Merkdum_{t-1}$	20,207	0.795	1	N/A
$MEFdum_{t-1}$	20,207	0.249	0	N/A
MVE_{t-1}	20,207	4,936	366	15,918
$StdRet_{t-1}$	20,207	0.150	0.128	0.092
$Analysts_{t-1}$	20,207	3.634	0	6.183
IO_{t-1}	20,207	0.486	0.512	0.325
M/B_{t-1}	20,207	2.195	1.655	1.681
$Leverage_{t-1}$	20,207	0.162	0.102	0.190
$StdEarn_{t-1}$	20,207	0.133	0.065	0.178
ΔEPS_{t-1}	20,207	0.037	0.007	0.283
$ISSUE_{t-1}$	20,207	0.081	0	N/A

Panel B: Pairwise correlations of main variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. TPP_{t-1}		**0.14**	**0.13**	**-0.06**	**0.11**	**-0.21**	**-0.02**	**0.05**	**-0.19**	**-0.56**	**0.29**	**-0.21**	**-0.23**	0.01	**-0.26**	**0.29**	0.01	**0.04**
2. $LLMComp_{t-1}$	**0.08**		**0.13**	**0.14**	**0.18**	**-0.02**	**0.13**	**0.06**	**-0.02**	**-0.06**	**0.05**	**0.10**	**-0.02**	**0.06**	**-0.22**	**0.08**	0.02	0.00
3. $Fluidity_{t-1}$	**0.10**	**0.06**		**0.33**	**0.47**	**-0.09**	**0.30**	**0.07**	**-0.08**	0.01	**0.22**	**0.27**	**-0.05**	**0.26**	**-0.14**	**0.34**	**0.02**	**0.12**
4. $Log(1+PDwords_t)$	**-0.07**	**0.13**	**0.32**		**0.28**	**0.04**	**0.49**	**0.06**	**0.04**	**0.20**	**0.03**	**0.74**	**0.09**	**0.20**	**-0.14**	**0.13**	0.02	**0.05**
5. $Log(1+Merkley_t)$	**0.10**	**0.10**	**0.41**	**0.23**		**0.03**	**0.23**	**0.48**	**0.04**	**-0.13**	**0.21**	**0.22**	**0.19**	**0.24**	**-0.19**	**0.29**	0.01	**0.12**
6. $MEFFreq_t$	**-0.22**	0.00	**-0.09**	**0.04**	**0.04**		**0.04**	**0.13**	**0.72**	**0.35**	**-0.27**	**0.21**	**0.38**	**0.10**	**0.13**	**-0.30**	**-0.04**	**-0.05**
7. $PDdum_{t-1}$	**-0.04**	**0.11**	**0.32**	**0.60**	**0.22**	**0.05**		**0.04**	**0.03**	**0.11**	**0.07**	**0.44**	**0.03**	**0.17**	**-0.13**	**0.17**	**0.02**	**0.05**
8. $Merkdum_{t-1}$	**0.06**	**0.07**	**0.03**	**0.05**	**0.75**	**0.12**	**0.04**		**0.13**	**-0.11**	**0.07**	**0.07**	**0.19**	**0.10**	**-0.08**	**0.10**	0.00	**0.05**
9. $MEFdum_{t-1}$	**-0.18**	0.00	**-0.08**	**0.04**	**0.06**	**0.70**	**0.03**	**0.13**		**0.31**	**-0.24**	**0.17**	**0.37**	**0.06**	**0.12**	**-0.28**	**-0.05**	**-0.05**
10. $log(MVE_{t-1})$	**-0.55**	0.01	**0.02**	**0.22**	**-0.16**	**0.36**	**0.15**	**-0.16**	**0.30**		**-0.49**	**0.41**	**0.43**	**0.24**	**0.24**	**-0.48**	0.00	**-0.07**
11. $StdRet_{t-1}$	**0.23**	-0.01	**0.19**	0.01	**0.15**	**-0.24**	**0.06**	**0.06**	**-0.20**	**-0.43**		**-0.10**	**-0.27**	-0.01	**-0.11**	**0.55**	**0.09**	**0.10**
12. $Log(1+Analysts_{t-1})$	**-0.23**	**0.10**	**0.25**	**0.72**	**0.18**	**0.25**	**0.41**	**0.07**	**0.20**	**0.46**	**-0.12**		**0.33**	**0.18**	**-0.04**	**-0.02**	**-0.02**	**0.05**
13. IO_{t-1}	**-0.23**	0.00	**-0.04**	**0.11**	**0.25**	**0.37**	**0.07**	**0.31**	**0.38**	**0.41**	**-0.28**	**0.36**		**0.09**	**0.07**	**-0.30**	**-0.05**	**-0.05**
14. M/B_{t-1}	**0.05**	0.00	**0.25**	**0.14**	**0.19**	**0.00**	**0.14**	**0.08**	**-0.02**	**0.09**	**0.12**	**0.08**	-0.01		**-0.15**	**0.16**	**0.11**	**0.07**
15. $Leverage_{t-1}$	**-0.17**	**-0.14**	**-0.04**	**-0.10**	**-0.11**	**0.09**	**-0.10**	**-0.05**	**0.08**	**0.15**	0.01	-0.01	**0.06**	**-0.05**		**-0.20**	**-0.02**	**-0.02**
16. $StdEarn_{t-1}$	**0.17**	0.00	**0.28**	**0.09**	**0.20**	**-0.20**	**0.14**	**0.09**	**-0.19**	**-0.36**	**0.43**	**-0.06**	**-0.28**	**0.32**	**-0.03**		**0.09**	**0.12**
17. ΔEPS_{t-1}	0.01	0.00	0.00	0.01	-0.01	**-0.05**	0.00	-0.01	**-0.04**	0.01	**0.06**	**-0.02**	-0.01	0.02	0.01	**0.04**		0.01
18. $ISSUE_{t-1}$	0.02	**-0.04**	**0.19**	**0.09**	**0.19**	**-0.05**	**0.06**	**0.10**	**-0.05**	**-0.09**	**0.12**	**0.03**	**-0.04**	**0.12**	**0.03**	**0.15**	0.00	

Note: Panel A presents the descriptive statistics of our sample firm-years. See variable definitions in Appendix 5. Panel B presents the pairwise correlations of variables using all available observations. We present Pearson correlations in the lower triangle and Spearman correlations in the upper triangle. The correlation coefficients that are statistically significant at 5% are in bold.

TABLE 3
Technological Peer Pressure and Future Performance

Panel A: Relation between technological peer pressure and future accounting performance

$Y_{t\ to\ t+2}$ =	$IndAdjROA_{t\ to\ t+2}$	$SalesGrowth_{t\ to\ t+2}$	$MarketShare_{t\ to\ t+2}$
TPP_{t-1}	-4.100***	-1.986**	-0.169***
	(-3.52)	(-2.20)	(-4.84)
Y_{t-1}	0.590***	-0.017**	0.968***
	(26.59)	(-2.41)	(61.58)
$StdY_{t-1}$	-0.020***	0.034***	0.018
	(-3.79)	(2.70)	(0.15)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj.R^2	43.1%	6.9%	9.6%
N	18,906	18,906	18,906

Panel B: Relation between technological peer pressure and future patent grants

$Y_{t\ to\ t+2}$ =	$Total\ Patents_{t\ to\ t+2}$	$Patent\ Value_{t\ to\ t+2}$
TPP_{t-1}	-0.308***	-0.359***
	(-10.96)	(-9.21)
Log(MVE_{t-1})	0.952***	1.700***
	(22.69)	(30.07)
ROA_{t-1}	-0.668***	-0.692***
	(-3.18)	(-2.99)
M/B_{t-1}	-0.119***	-0.124***
	(-4.16)	(-3.72)
Intercept	-1.484	-9.115***
	(-0.76)	(-3.66)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Adj. R^2	50.9%	54.85%
N	17,191	17,191

Note: *ROA* is the firm's accounting return on total assets. $IndAdjROA_{t\ to\ t+2}$ is the firm's industry-adjusted (subtracting the median *ROA* of firms in the sample firm's 4-digit SIC) *ROA* averaged for years *t* to *t*+2. $SalesGrowth_{t\ to\ t+2}$ is the firm's percentage change in annual sales averaged for years *t* to *t*+2. $MarketShare_{t\ to\ t+2}$ is the firm's sales divided by total sales in the firm's 4-digit SIC industry averaged for years *t* to *t*+2. $Total\ Patents_{t\ to\ t+2}$ is the natural logarithm of 1 plus the total number of patents granted to the firm in years t to t+2. $Patent\ Value_{t\ to\ t+2}$ is the natural logarithm of 1 plus the total estimated dollar value of patents granted to firm *i* during years *t* to *t*+2 scaled by the firm's market value of equity at the beginning of fiscal year *t*. We obtain information about patents and their estimated dollar values from the website maintained by Professor Noah Stoffman (https://iu.app.box.com/v/patents). *Y* represents the industry-adjusted *ROA*, sales growth, and market share, respectively. The measurement of *StdY* uses at least three observations. See the definitions of *TPP*, *MVE*, and *M/B* in Appendix 5. We report *t*-statistics in parenthesis, with standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 4
Market Reaction to Product Disclosure Press Releases

Panel A: Descriptive statistics of product disclosure and return reaction to the disclosure event

	Mean	Median	Std. Dev.
1-day CAR	0.326***	0.033***	3.385
	(32.52)	(16.54)	
3-day CAR	0.381***	0.018***	5.559
	(23.20)	(9,81)	
#Words	260	109	245

Panel B: Regressing return reaction on product disclosure

	1-day CAR	*3-day CAR*
Log(#Words)	0.053***	0.057**
	(3.66)	(2.40)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Adj.R^2	1%	1%
N	85,916	85,929

Note: The observations used for this table are at the press release level. We obtained 240,663 press releases of product disclosure with Compustat identifiers issued by 56,326 firm-years, including international and over-the-counter stocks, during 2002–2012. After merging with our *TPP* sample, we are left with 85,929 press releases. *#Words* is the total number of words (including numbers) in a given product disclosure press release after common stop words are excluded. In contrast, our product disclosure measure in the primary analysis—*PDwords*—is at the firm-year level and measured as the total number of words in all product disclosure press releases issued by the sample firm during the fiscal year. *1-day CAR* is the firm's stock return on the trading day of the press release minus the index return of firms in the same size portfolio formed at the end of the previous calendar year. *3-day CAR* is the firm's buy-and-hold return from one trading day before the press release to one trading day after the release minus the buy-and-hold return of the index return of firms in the same size portfolio over the same 3-day window. We estimate OLS regressions with standard errors clustered by firm and report *t*-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5
Comparing Technological Peer Pressure with Other Firm-specific Competition Measures

Panel A: Pairwise correlations of the technological peer pressure (*TPP*) measure with the other measures

	TPP	*LLMComp*	*Fluidity*
TPP		0.139***	0.126***
LLMComp	0.080***		0.134***
Fluidity	0.101***	0.060***	

Panel B: Sorting sample into quintiles by *TPP*

Quintiles	*TPP*	*LLMComp*	*Fluidity*
5 (highest)	7.699	1.244	7.284
4	5.826	1.233	8.444
3	4.636	1.233	8.222
2	3.097	1.144	7.049
1 (lowest)	0.700	1.114	6.603
Diff (5 - 1)		0.130	0.682
t-statistic		8.54***	8.50***

Note: The tables use the 16,404 sample firm-year observations that have *TPP*, *LLMComp*, and *Fluidity* measures available. See variable definitions in Appendix 5. Panel A reports pairwise Pearson (Spearman) correlations in the lower (upper) triangle. In Panel B, we sort the sample firm-years into five quantiles each year based on the value of *TPP* and report the mean values of *TPP*, *LLMComp*, and *Fluidity* for each quintile. At the end of the table, we compare the values of *LLMComp* and *Fluidity* in the highest *TPP* quintile with those in the lowest *TPP* quintile and report the *t*-statistic for the between-group T test. *** indicates statistical significance at the 1% level.

TABLE 6
Comparing Product Disclosure and Other Voluntary Disclosure Measures

Panel A: Pairwise correlations of the product disclosure measure (*PDwords*) with the other measures

	Log (1+PDwords)	*Log (1+Merkley)*	*MEFFreq*
Log (1+PDwords)		0.288***	0.038***
Log (1+Merkley)	0.227***		0.027***
MEFFreq	0.044***	0.045***	

Panel B: Sorting sample into groups by the product disclosure measure

Groups	*PDwords*	*Merkley*	*MEFFreq*
5 (highest)	4,397.5	25.2	1.126
4	2,076.0	24.7	0.968
3	1,061.6	21.1	0.967
2	527.3	17.5	0.997
1	137.9	13.4	0.893
0 (lowest)	0	11.9	0.843
Diff (5 - 0)		13.3	0.282
t statistic		35.1***	6.39***

Note: The tables use the 16,864 sample firm-year observations that have *PDwords*, *Merkley*, and *MEFFreq* measures available. See variable definitions in Appendix 5. Panel A reports pairwise Pearson (Spearman) correlations in the lower (upper) triangle. In Panel B, we first separate the 8,998 firm-years with zero values of *PDwords* and then sort the remaining sample firm-years into five quantiles each year based on the value of *PDwords.* We report the mean values of *PDwords*, *Merkley*, and *MEFFreq* for each group and compare the values of *Merkley* and *MEFFreq* in the highest *PDwords* group with those in the lowest *PDwords* group. At the end of the table, we report the *t*-statistic for the between-group T test. *** indicates statistical significance at the 1% level.

TABLE 7
Competition and Product Disclosure—Regression Analysis

	Dependent variable $= Log(1+PDwords_t)$				
	(1)	(2)	(3)	(4)	(5)
TPP_{t-1}	-0.838^{***}	-0.593^{***}			-0.478^{***}
	(-5.96)	(-5.12)			(-3.80)
$LLMComp_{t-1}$			0.108		0.076
			(1.24)		(0.85)
$Fluidity_{t-1}$				0.928^{***}	0.889^{***}
				(8.41)	(7.84)
$PDdum_{t-1}$		1.822^{***}	1.835^{***}	1.765^{***}	1.743^{***}
		(20.58)	(18.60)	(18.32)	(17.65)
$Log(MVE_{t-1})$	0.016	0.094^{***}	0.172^{***}	0.159^{***}	0.117^{***}
	(0.71)	(4.81)	(6.86)	(6.45)	(4.42)
$StdRet_{t-1}$	1.181^{***}	0.747^{***}	0.698^{***}	0.415^{*}	0.410^{*}
	(4.67)	(3.39)	(3.04)	(1.82)	(1.82)
$Log(1+Analysts_{t-1})$	1.575^{***}	1.034^{***}	1.051^{***}	1.045^{***}	1.048^{***}
	(39.91)	(24.69)	(21.79)	(22.26)	(21.82)
IO_{t-1}	0.023^{***}	0.021^{***}	-0.246^{*}	-0.294^{**}	-0.293^{**}
	(4.09)	(7.98)	(-1.94)	(-2.35)	(-2.28)
M/B_{t-1}	0.043^{***}	0.034^{***}	0.007	0.007	0.013
	(2.90)	(2.75)	(0.46)	(0.48)	(0.85)
$Leverage_{t-1}$	-0.220^{***}	-0.209^{***}	-0.105^{*}	-0.118^{**}	-0.129^{**}
	(-3.54)	(-3.41)	(-1.94)	(-2.12)	(-2.32)
$StdEarn_{t-1}$	0.117	0.058	0.085	0.032	-0.008
	(1.15)	(0.71)	(1.00)	(0.40)	(-0.10)
ΔEPS_{t-1}	0.030	0.032^{*}	0.025	0.031	0.031
	(1.63)	(1.79)	(1.16)	(1.38)	(1.37)
$ISSUE_{t-1}$	0.773^{***}	0.764^{***}	0.799^{***}	0.728^{***}	0.731^{***}
	(8.05)	(9.48)	(9.71)	(9.03)	(8.90)
Intercept	0.708	0.027	-0.545	-0.491	-0.154
	(1.24)	(0.06)	(-1.23)	(-0.75)	(-0.23)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	45.4%	48.2%	48.6%	48.9%	48.7%
N	20,207	20,207	16,861	17,029	16,404

Note: The table presents the OLS estimations with standard errors robust to heteroskedasticity and clustered by firm. *PDwords* is the total number of words in the firm's product disclosure press releases issued during fiscal year *t*. All independent variables are measured at the beginning of year *t*. See Appendix 5 for other variable definitions. We use the decile ranked variables, ranging from 0 to 1, of *TPP, LLMComp,* and *Fluidity* in the regressions, and report *t*-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8
R&D Intensity and the Association between *TPP* and Product Disclosure

Panel A: Controlling for R&D intensity

$Y = \log(1+PDwords_t)$	(1)	(2)	(3)
TPP_{t-1}	-0.593***		-0.356***
	(-5.12)		(-2.97)
G_{t-1}/TA_{t-1}		0.304***	0.265***
		(6.87)	(5.80)
$PDdum_{t-1}$	1.822***	1.744***	1.739***
	(20.58)	(19.2)	(19.12)
Other controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adjusted R^2	48.3%	48.2%	48.4%
N	20,207	20,207	20,207

Panel B: Partitioning the sample into quintiles by R&D intensity

	Quintile 1 (lowest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (highest)
TPP_{t-1}	-0.620**	-0.517*	-0.614*	-0.834**	-0.920***
	(-2.08)	(-1.76)	(-1.82)	(-2.55)	(-2.59)
$PDdum_{t-1}$	1.680***	2.429***	3.291***	3.395***	3.444***
	(9.05)	(16.43)	(21.19)	(16.39)	(17.86)
Other controls	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	39.1%	0.426	0.496	0.437	0.377
N	4,047	4,041	4,040	4,041	4,038

Note: We measure a firm's R&D intensity, *G/TA*, at the beginning of year *t* as its R&D stock divided by the total assets and winsorize the variable at the 1% and 99% of the distribution. In Column 1 of Panel A we reproduce the estimation results of Column 2 of Table 7. In Column 2 we add *G/TA* but exclude *TPP* to see the effect of *G/TA* alone. In Column 3, we add back *TPP*. In Panel B we estimate Equation (4) using each quintile of R&D intensity. See other variable definitions in Appendix 5. We use the full-sample decile-ranked variable, ranging from 0 to 1, of *TPP* in the regressions. We report the OLS estimations with *t*-statistics in parentheses and standard errors robust to heteroskedasticity and clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 9
Technological Peer Pressure and Other Voluntary Disclosure—Regression Analysis

	Dependent Var. = *Log(1+Merkley$_t$)*				Dependent Var. = *MEFFreq$_t$*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPP$_{t-1}$	-0.402***			-0.477***	-0.014			0.031
	(-5.18)			(-8.51)	(-0.28)			(0.53)
LLMComp$_{t-1}$		0.125***		0.097**		-0.035		0.000
		(2.97)		(2.45)		(-0.60)		(0.00)
Fluidity$_{t-1}$			0.684***	0.709***			-0.364***	-0.386***
			(12.22)	(15.75)			(-6.15)	(-6.43)
LagYdum$_{t-1}$	2.357***	1.096***	1.766***	1.033***	2.666***	2.628***	2.616***	2.597***
	(68.75)	(18.68)	(24.09)	(18.18)	(52.59)	(51.08)	(51.29)	(50.32)
Log(MVE$_{t-1}$)	-0.103***	-0.003	-0.021*	-0.053***	0.089***	0.176***	0.176***	0.184***
	(-6.78)	(-0.30)	(-1.85)	(-5.07)	(8.02)	(10.15)	(10.28)	(10.21)
StdRet$_{t-1}$	0.511***	0.608***	0.320***	0.342***	-0.821***	-0.962***	-0.755***	-0.777***
	(4.25)	(6.29)	(3.69)	(4.64)	(-7.49)	(-7.72)	(-6.22)	(-6.20)
Log(1+Analysts$_{t-1}$)	0.180***	0.018	-0.027	0.014	0.099***	0.085***	0.098***	0.104***
	(7.16)	(1.37)	(-1.58)	(1.13)	(5.35)	(4.01)	(4.72)	(4.80)
IO$_{t-1}$	0.027	0.241***	0.228***	0.204***	0.232***	-0.229***	-0.198**	-0.202**
	(0.77)	(4.47)	(3.57)	(4.10)	(4.86)	(-2.82)	(-2.49)	(-2.48)
M/B$_{t-1}$	0.026	0.015***	0.022***	0.019***	0.011	-0.007	-0.002	-0.004
	(1.36)	(2.96)	(3.77)	(4.13)	(1.49)	(-0.80)	(-0.25)	(-0.43)
Leverage$_{t-1}$	-0.055	-0.048**	-0.063**	-0.063***	0.257***	0.297***	0.271***	0.270***
	(-1.44)	(-2.21)	(-2.04)	(-2.62)	(3.96)	(4.14)	(3.86)	(3.73)
StdEarn$_{t-1}$	0.105**	0.100***	0.038	0.014	-0.136**	-0.135**	-0.042	-0.020
	(2.15)	(3.11)	(1.23)	(0.58)	(-2.34)	(-2.14)	(-0.66)	(-0.30)
ΔEPS$_{t-1}$	-0.013**	-0.003	-0.005	-0.000	-0.001	-0.013	-0.022	-0.025
	(-2.16)	(-0.73)	(-0.91)	(-0.05)	(-0.04)	(-0.45)	(-0.80)	(-0.90)
ISSUE$_{t-1}$	0.452***	0.166***	0.106***	0.101***	-0.035	-0.051	-0.022	-0.015
	(9.43)	(6.02)	(2.83)	(3.89)	(-1.01)	(-1.43)	(-0.62)	(-0.42)
Intercept	1.576***	1.213**	1.246*	1.505**	0.263	0.290	0.221	0.172
	(3.22)	(2.03)	(1.85)	(2.26)	(0.28)	(0.24)	(0.20)	(0.15)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj./Pseudo R^2	32.3%	59.0%	46.6%	62.4%	52.9%	53.3%	53.5%	53.4%
N	20,207	16,861	17,029	16,404	20,207	16,861	17,029	16,404

Note: We use the OLS estimations when the dependent variable is *Log(1+Merkley)* and use the generalized negative binomial estimations when the dependent variable is *MEFFreq.* We report the *z*- or *t*-statistics in parentheses with standard errors robust to heteroskedasticity and clustered by firm. *LagYdum* is *Merkdum* when the dependent variable is *Log(1+Merkley)* and is *MEFdum* when the dependent variable is *MEFFreq*. See variable definitions in Appendix 5. We use the decile ranked variables, ranging from 0 to 1, of *TPP, LLMComp,* and *Fluidity* in the regressions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 10
Technological Peer Pressure and Alternative Measures of Product Disclosure

Dependent Var. =	*PDFreq*$_t$ Negative Binomial (1)	*Log(1+PDwords*$_t$*)* (R&D stage) OLS (2)	*Log*(1+*PDwords*$_t$*)* (Product intro) OLS (3)	*Log*(1+*PDwords*$_t$*)* (Product improvement) OLS (4)
TPP_{t-1}	-0.553***	-0.735***	-0.450***	-0.523***
	(-6.77)	(-6.16)	(-4.10)	(-5.49)
$PDdum_{t-1}$	1.360***	1.113***	1.193***	0.681***
	(25.80)	(14.20)	(15.43)	(10.28)
$Log(MVE_{t-1})$	0.206***	0.098***	0.159***	0.111***
	(13.93)	(5.06)	(8.44)	(6.14)
$StdRet_{t-1}$	0.539***	0.795***	0.185	0.213
	(3.91)	(3.72)	(0.89)	(1.08)
$Log(1+Analysts_{t-1})$	0.255***	0.735***	0.813***	0.795***
	(11.98)	(18.19)	(19.98)	(21.02)
IO_{t-1}	0.006*	0.014	0.021***	0.024***
	(1.89)	(1.51)	(6.91)	(9.07)
M/B_{t-1}	0.005	0.021	-0.007	0.003
	(0.61)	(1.60)	(-0.65)	(0.16)
$Leverage_{t-1}$	-0.052	-0.143***	-0.047	-0.031
	(-1.03)	(-2.87)	(-1.00)	(-0.63)
$StdEarn_{t-1}$	0.111**	-0.014	0.161**	0.112
	(2.34)	(-0.18)	(2.08)	(1.44)
ΔEPS_{t-1}	0.003	0.027**	0.011	0.016
	(0.39)	(2.13)	(0.79)	(1.00)
$ISSUE_{t-1}$	0.221***	0.706***	-0.054	0.085
	(5.20)	(8.24)	(-0.72)	(1.11)
Intercept	-2.667***	-0.043	-0.881***	-0.674***
	(-6.90)	(-0.08)	(-4.61)	(-3.19)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adj./pseudo R^2	17.5%	40.2%	41.8%	36.1%
N	20,207	20,2%07	20,207	20,207

Note: We reestimate Equation (4), Column 2 of Table 7, using alternative measures of product disclosure. We estimate a generalized negative binomial model (GNBREG in Stata) when the dependent variable is *PDFreq*. We report the *z*- or *t*-statistics in parentheses with standard errors robust to heteroskedasticity and clustered by firm. See variable definitions in Appendix 5. We use the decile ranked variable, ranging from 0 to 1, of *TPP* in the regressions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 11
Cross-sectional Variation in the Association of *TPP* with Product Disclosure

Dependent Variable = $Log(1+PDwords_t)$	Technology factor		Customer concentration		Stage of life cycle	
	High-tech	Other	High	Low	Introduction & Growth	Mature, Shake-out, & Decline
TPP_{t-1}	-0.692**	-0.558***	-0.849***	-0.451***	-0.697***	-0.461***
	(-2.39)	(-4.44)	(-5.36)	(-2.92)	(-4.27)	(-3.36)
$PDdum_{t-1}$	2.382***	1.706***	1.697***	1.870***	1.559***	1.348***
	(10.55)	(17.57)	(14.65)	(15.39)	(11.70)	(13.29)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	39.4%	47.7%	47.9%	48.3%	44.9%	52.0%
N	3,406	16,801	10,106	10,101	7,758	12,449
Test of coefficient on *TPP*:						
χ^2 (p-value)	3.56* (0.059)		4.70** (0.030)		4.57** (0.032)	

Note: We estimate Equation (4) using subsamples partitioned by (1) the technology factor, (2) customer concentration, and (3) litigation risk, respectively. We sort the sample into "high-tech firms" vs. "other firms," where high-tech firms are Pharmaceuticals, Computer Hardware, and Telecommunications Equipment firms according to Bloom et al.'s (2013) online Appendix F. These firms encompass 11 industries defined by the 4-digit SIC codes (see details in Footnote 35). We follow Dhaliwal et al. (2016) and calculate customer concentration using firms' mandatory disclosure of major customers available in Compustat's Segment database. Customer concentration is the sum of the squared proportion of the firm's total sales in fiscal year *t*-1 to each disclosed customer (in a similar way as how the Herfindahl index is calculated). We classify the firm-years with above sample median value of customer concentration as "high" concentration firms. Low customer concentration firms include those without any major customers. For the life-cycle test, we follow Dickinson (2011) and classify sample firm-years into five stages of the life cycle: (1) introduction, (2) growth, (3) mature, (4) shake-out, and (5) decline based on the cash flow patterns. We then combine the early stages (stages 1 & 2) and later stage (stages 3, 4, & 5) separately. See other variable definitions in Appendix 5. We use the decile ranked variable, ranging from 0 to 1, of *TPP* in the regressions. We report the OLS estimations with *t*-statistics in parentheses and standard errors robust to heteroskedasticity and clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 12
Instrumental Variable Estimation for the Relation between *TPP* and Product Disclosure

Dependent Variable = Log (1+$PDwords_t$)	OLS	IV	
		1st stage	2nd stage
$TaxCredit_{t-1}$		0.012**	
		(2.13)	
$UTSA_{t-1}$		0.004***	
		(9.88)	
TPP_{t-1}	-0.782***		-0.765*
	(-4.91)		(-1.87)
$PDdum_{t-1}$	1.721***	-0.045***	1.788***
	(14.85)	(-5.26)	(14.65)
Other control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	11,397	11,397	
Adjusted R^2	0.489	0.495	
Tests of weak identification:			
First-stage F-statistic (p-value)		49.12 (0.00)	
Cragg–Donald F-statistic		200.86	
Test of instrument exogeneity:			
Hansen J statistic (p-value)		2.424 (0.122)	

Note: We use the identification provided by (1) the introduction of state-level R&D tax credits and (2) the enactment of the Uniform Trade Secrets Act (UTSA). To construct the instrumental variables, we first decompose *TPP* into two components depending on whether a peer firm is headquartered in the same state as the sample firm.

$$TPP_{i,t} \equiv \log\left[1 + \frac{1}{G_{i,t}} \sum_{j \neq i} \omega_{ij} \times G_{j,t}\right] = \log\left[1 + \frac{1}{G_{i,t}} \left(\sum_{j \neq i} \omega_{ij} \times G_{j,t} \times \mathrm{I}(S_{j,t} \neq S_{i,t}) + \sum_{j \neq i} \omega_{ij} \times G_{j,t} \times \mathrm{I}(S_{j,t} = S_{i,t})\right)\right].$$

The first component encapsulates R&D activities conducted by peer firms headquartered outside of the state in which firm i is headquartered. The second component encapsulates R&D activities conducted by peer firms headquartered in the same state as firm i. Here, I is the indicator function and $S_{i,t}$ is the state in which firm i is headquartered. We construct two instruments:

$$TaxCredit_{i,t} \equiv \sum_{j \neq i} \omega_{ij}^{0} \times \mathrm{I}\left(TaxCredit(S_{j,t})\right) \times \mathrm{I}(S_{j,t} \neq S_{i,t})\,;\ UTSA_{i,t} \equiv \sum_{j \neq i} \omega_{ij}^{0} \times UTSA(S_{j,t}) \times \mathrm{I}(S_{j,t} \neq S_{i,t})$$

In the formulae, $\mathrm{I}\left(TaxCredit(S_{j,t})\right)$ indicates whether at the beginning of year t the state in which peer firm j is headquartered has introduced tax credit for qualified incremental R&D expenditures, $UTSA(S_{j,t})$ is the state-level index with a higher value representing stronger legal protection of trade secrets based on milestones that include both the UTSA taking effect and legal decisions that set precedent, and ω_{ij}^{0} is the closeness of firm j with firm *I,* calculated using segment sales in 2001 or the year preceding before both firms' first appearance in our sample if they do not enter the sample until after 2002. See other variable definitions in Appendix 5. The UTSA data is available until 2008. The number of observations is further decreased by the drop of Canadian firms and firms headquartered in Nebraska, for which UTSA information is unavailable. We use the decile ranked variable, ranging from 0 to 1, of *TPP* in the estimation, and report *t*-statistics in parentheses with standard errors robust to heteroskedasticity and clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.