Product Market Competition, Proprietary Costs, and Disclosure Differentiation

Junqi Liu
junqi.liu@essec.edu
ESSEC Business School

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Abstract: This study examines whether and how product market competition with existing rivals affects the content of a firm's disclosures relative to the disclosures of industry peers. I use a topic-modeling technique to extract and compare the thematic topics in MD&A disclosure in 10-K filings between industry peers. Exploiting large reductions in U.S. import tariff rates to identify exogenous increases in product market competition for domestic firms, I find that firms differentiate disclosure topics from peers after an increase in product market competition with existing rivals. The impact is more pronounced when the tariff rate reduction triggers a greater increase in competition and when the disclosure likely incurs higher proprietary costs. I also document that disclosure-differentiating firms exhibit better future performance in the product market relative to their peers but that investors do not seem to value this differentiation. My findings suggest that competition with existing rivals causes firms to differentiate their disclosure to protect proprietary information.

Key words: Disclosure; MD&A; Product market competition; Proprietary costs; Textual analysis; Topic modelling; Machine learning

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1. Introduction

This study investigates how product market competition with existing rivals affects firms' choices about the content of disclosures relative to the content of their competitors' disclosures. In particular, I examine whether a firm facing increased product market competition with existing rivals differentiates the topics covered in its disclosures from those of its industry peers, that is, to make the thematic content of its disclosure more different from that of its peers, in order to protect the firm's proprietary information.

The question of how firms defend themselves against their rivals has received ample attention in accounting, economics, finance, and management literatures (Fudenberg and Tirole 1986; Frésard 2010; Zingales 1998; Teece, Pisano, and Shuen 1997; Jiang, Levine, and Lin 2016). Particularly in recent decades, the effect of product market competition on managerial disclosure decisions has generated heated debate in accounting research. Theory predicts that competition with existing rivals reduces discretionary disclosure that might reveal proprietary information, such as pricing terms and trade secrets, and assist active competitors (Verrecchia 1983, 1990; Clinch and Verrecchia 1997). For example, in a market with partially differentiated products, firms will mimic the strategy of successful competitors and introduce more profitable product lines; even in a price-competition market with identical products, firms informed of competitors' pricing terms will gain a second-mover advantage. However, empirical findings on the relation between competition and disclosure are very mixed (e.g., Berger 2011; Botosan and Stanford 2005; Li 2010; Huang, Jennings, and Yu 2017).

Notably, while prior literature largely focuses on the supply of voluntary disclosure, I revisit the relation between product market competition and disclosure from a novel perspective: the semantic meaning of disclosure. Though firms are able to reduce discretionary disclosure to protect proprietary information from competitors, doing so likely incurs costs, including lower stock liquidity (e.g., Balakrishnan, Billings, Kelly, and Ljungqvist 2014) and higher cost of capital (Francis, Nanda, and Olsson 2008). Moreover, regulations that mandate the minimum quantity and quality of corporate disclosure (e.g., annual financial reporting) prevent firms from arbitrarily reducing their supply of disclosure. Given these constraints, whether firms can protect proprietary information through methods other than disclosure cuts becomes a pressing question.

Empirical evidence shows that in addition to reducing the quantity and quality of its supply of disclosures (e.g., Berger and Hann 2007; Huang et al. 2017), a firm can hide information by increasing the processing cost of disclosures (Blankespoor, deHaan, and Marinovic 2020). For example, Rahman, Ali, Duong, and Oliver (2019) find that firms exert effort to protect proprietary information by reducing the readability of their annual reports. To the extent that the similarity of the disclosure can help information users identify a firm's industry peers (Hoberg and Phillips 2016) and comprehend the firm's released information by comparing it to that of its peers (e.g., Baginski 1987; Shroff, Verdi, and Yost 2017), disclosure with highly differentiated content would be less comparable to disclosure by the firm's peers and, thus, increases competitors' costs of processing such disclosure. Indeed, Chircop, Collins, Hass, and Nguyen (2020) show that accounting comparability between industry peers facilitates their learning from peers. As such, a firm may protect its proprietary information by *differentiating* the content of its disclosures from that of its rivals' disclosures. This prediction is also consistent with the finding in the literature of psychology that disclosers tend to adopt evasive tactics to avoid or minimize accountability pressure (Green, Visser, and Tetlock 2000) and discuss irrelevant or excessively general topics to dilute the disclosure of potentially sensitive information (e.g., Hurtig 1977; Harris 1991). In the context of product market competition, deviating from the topic set covered by peer firms likely helps a firm distract rivals' attention from topics of "common concern" and consequently reduces the proprietary costs of disclosure.

On the other hand, firms facing competition might well provide "mean-reverting" disclosure with content similar to that provided by peer firms in order to avoid revealing incrementally new information. Thus, the relation between product market competition and a firm's topic difference from its rivals is an empirical question.

I empirically capture disclosure differentiation by comparing the *topic difference* between peer firms' disclosures. Referring to the difference in semantic content between peer firms' disclosure narratives, topic difference measures how different a text is relative to other texts in terms of topic coverage. In this sense, the topic difference of a firm's disclosure from those of other firms is a *relative* characteristic of the firm's disclosure. Prior studies on the effect of product market competition on firm disclosures focus mostly on *absolute* metrics of the quantity or quality of firms' disclosures, independent of other firms' disclosures. For examples, product market competition is found to be related to the frequency and biases of management forecasts (Li 2010; Huang et al. 2017), the frequency of press releases (Burks, Cuny, Gerakos, and Granja 2018), the readability of annual reports (Rahman et al. 2019), and disclosure redaction (Verrecchia and Weber 2006). In contrast, much less is known about whether and how firms change their disclosure behaviors *relative* to peer firms in response to variations in product market competition. As product market competition among rival firms is a multiplayer game, the strategy of each player depends on the strategies of all other players. Thus, one firm's choice on disclosure is likely not only determined by the competition per se, but also shaped by the choices of other competitors. As a result, it would be meaningful to investigate a firm's disclosure decisions relative to the decisions of its competitors.[1]

I extract and compare the topics that firms discuss in disclosures using a textual analysis of the management discussion and analysis section (MD&A) of 10-K reports. MD&As are an appropriate form of disclosure for my analysis because they are *mandatory*, yet allow significant managerial discretion on content and language (Feldman, Govindaraj, Livnat, and Segal 2010; Brown and Tucker 2011). The mandatory nature of MD&A ensures the availability and quality of the disclosure, while managerial discretion provides variations for my analysis. I employ a topic modelling technique to compare the content of a large sample of MD&A narratives. This automated comparison allows me to *quantify* the topic difference between firms' disclosures. I first validate MD&A disclosure topic difference as a reliable measure of how much a firm's disclosure content differs from that of its peers. Particularly, the disclosure topic difference is smaller for firm pairs in the same industry and/or in the same year. Furthermore, the topic difference of a firm relative to its industry peers is negatively associated with disclosure length and the firm's fundamental similarity (captured by the co-movement of stock returns) with its peers. In addition, I find disclosure topic difference to be negatively associated with industry concentration (as measured by the Herfindahl index), providing some evidence for the disclosure differentiation hypothesis. Lastly, I also demonstrate that that higher MD&A disclosure topic difference likely leads to higher processing costs of disclosure.

Exploiting large reductions in U.S. import tariff rates as plausibly exogenous shocks to product market competition (e.g., Frésard 2010; Valta 2012) and using a difference-in-differences

[1] Aobdia and Cheng (2018) provide an interesting example depicting the relative disclosure characteristics: though firms in unionized industries typically have an incentive to withhold information from capital markets to preserve their bargaining power when negotiating with labor unions (Hilary 2006; Bova, Dou, and Hope 2015), non-unionized firms in unionized industries disclose more information when their unionized rivals are engaged in labor renegotiations in order to weaken competitors.

(diff-in-diff) design, I document an increase in disclosure topic difference for firms experiencing a tariff reduction relative to firms that do not experience the reduction. Specifically, a tariff reduction leads to an increase in the topic difference of an average firm's disclosure by one-third standard deviation, which is economically meaningful. I also find greater impact for industries in which the tariff rate reduction triggers a larger increase in imports and for industries with a larger amount of imports before the tariff reduction, consistent with disclosure content differentiation arising from tariff reductions. Furthermore, I establish that the increase is stronger for firms with higher profit margins and/or market share within their industry, indicating that the topic difference in disclosures increases more when the disclosure likely incurs higher proprietary costs. The increase in topic difference of disclosure is also more pronounced in firms with higher fundamental similarity to their industry peers, suggesting that firms are more prone to differentiate the content of disclosure from their competitors when facing likely more fierce competition and therefore having higher concerns about proprietary costs. Finally, the increase in topic difference of disclosures is stronger for lengthier disclosures. To the extent that lengthier disclosures likely convey more information (e.g., Jiang, Pittman, and Saffar 2019), this result suggests that content differentiation is a potential substitute for withholding information through shorter disclosures. In sum, these findings unanimously support the conjecture that firms may intentionally differentiate the content of their disclosure from those of their rivals to reduce the proprietary costs of disclosure.

I perform a battery of additional analyses to challenge the robustness of my findings. The results from a propensity-score-matched sample reveal that my findings are robust to the concern of firms' self-selecting industries. A placebo test that forces the tariff reduction events to three years earlier than the actual events lends support to the causal inference using tariff rate reductions as a plausibly exogenous shock to product market competition. In addition, a test of the dynamics of the impact of tariff rate reductions further ensures that the parallel trend assumption is met.

Finally, I explore the consequences of disclosure content differentiation induced by increased market competition. Firms that disclose more different topics after tariff reductions achieve higher percentiles of future market shares and profitability than their peers, but do not outperform in firm valuation. Furthermore, I find that investors of firms that differentiate disclosure topics more than their rivals after tariff reductions do not gain abnormal returns surrounding the 10-K filing date. Together, the results indicate that differentiated disclosure content helps to protect proprietary information and defend product market competitiveness (Boone, Floros, and Johnson 2016), but investors do not value disclosure differentiation, probably due to increased processing costs. Complementing this finding with a path analysis, I show that higher disclosure topic difference does not lead to a higher fundamental difference of the firm from its peers, rejecting the possible alternative explanation that an increase in topic difference of disclosures signals differentiated business in the future.

Overall, I establish that in response to an increase in product market competition with existing rivals, firms differentiate their disclosure content by increasing the difference in the topics discussed in the disclosures relative to their rivals in an attempt to reduce the proprietary costs of disclosure. My findings are consistent with the proprietary cost hypothesis (Verrechia 1983; Clinch and Verrecchia 1997) and add novel evidence to the ongoing debate regarding the impact of product market competition on firms' disclosure behaviors (e.g., Li 2010; Ali, Klasa, and Yeung 2014; Huang et al. 2017, Burks et al. 2018). The mixed empirical results on the relation between competition and disclosure in the prior literature potentially indicate the existence of missing pieces from the mosaic. I complement the extant discussion by documenting a formerly unexplored strategy used by firms in response to increased competition with existing rivals. Future studies may take into account the relation (e.g., complementarity or substitutability) between the quantity and content difference of disclosure, and design more powerful tests of the effects of competition on disclosure. Furthermore, by showing the influence of competition-induced disclosure on firms' relative market shares and profitability, this study adds to the broader discussion of how firms defend themselves against their rivals (e.g., Fudenberg and Tirole 1986; Frésard 2010; Zingales 1998; Teece et al. 1997; Jiang et al. 2016).

Moreover, this study reveals the relevance of the disclosure behaviors of a firm relative to those of its peers, an underexplored area in accounting research. To my best knowledge, this study is the first to capture the *topic difference* between financial texts in a large sample, uncovering a new dimension of corporate disclosure research that is worthy of further research. In addition, this study adds to the growing literature that uses machine learning techniques to analyze accounting and financial texts (e.g., Huang, Lehavy, Zang, and Zheng 2018; Dyer, Lang, and Stice-Lawrence 2017; Brown, Crowley, and Elliott 2020) by providing a new avenue to analyze and understand corporate disclosure behaviors. Lastly, this study may also be of interest to practitioners, as the stock market does not seem to value the topic-differentiation strategy in response to competition even if it helps defend the firm's competitiveness in the product market.

2. Related Literature and Hypotheses Development

2.1. Product market competition and firms' disclosure behaviors

In the absence of costs and market imperfections, value-maximizing managers would fully disclose their firms' private information (Grossman and Hart 1980). In practice, however, proprietary and agency costs are potential constraints to full disclosure. Verrecchia (1983) analytically shows that, in the presence of proprietary costs, partial disclosure can be optimal, with the level of disclosure decreasing in the proprietary costs of disclosure. Furthermore, Berger and Hann (2007) find that agency costs motivate managers to withhold segment information to hide their firm's profitability.

Theorists distinguish between competition with *existing rivals* and threat from *potential entrants*. As a firm's disclosures may release proprietary information that potentially helps existing competitors—such as pricing terms, details about its products or services, trade secrets, or purchase requirements—theorists typically conclude that product market competition with existing rivals has a negative impact on disclosures (Verrecchia 1983, 1990; Clinch and Verrecchia 1997).[2] By contrast, models of threat from potential entrants predict that a higher threat of entry will encourage the incumbent firm to disclose more so as to deter potential entries into the industry (e.g., Darrough and Stoughton 1990; Wagenhofer 1990). This study focuses particularly on product market competition with existing rivals.

Empirical results on the impact of product market competition on corporate disclosure behaviors are mixed. Early studies typically use industry concentration as a proxy for competition, leading to "fragility of inferences" (Berger 2011). Some studies find a negative relation between industry concentration and disclosure (Harris 1998; Botosan and Stanford 2005; Bamber and Cheon 1998), while others find positive (Verrecchia and Weber 2006) or statistically weak relations (Botosan and Harris 2000; Berger and Hann 2007; Bens, Berger, and Monahan 2011). As is discussed in Li, Lin, and Zhang (2018), theoretically, industry concentration can be either positively or negatively associated with proprietary costs of disclosure, depending on the form of competition (i.e., existing rivals versus threats of potential entrants). Empirically, the measure of

[2] Darrough (1993), an exception, shows that the relation between disclosures and product market competition with existing rivals and disclosure can vary according to the type of information (demand versus cost and good versus bad news) and the nature of competition (Cournot versus Bertrand).

industry concentration per se also creates problems. As noted by Ali et al. (2014), even when measured accurately, industry concentration is an indirect measure of competition; more importantly, it is unclear whether a higher level of industry concentration indicates more or less competition (see also, Lang and Sul 2014). Using Compustat data, Li (2010) proxies for the level of competition among rivals using a common factor extracted from two measures of industry concentration: market size and the number of firms in the industry. She finds that this factor is negatively related to disclosure quantity, while Ali, Klasa, and Yeung (2008, 2014) use U.S. Census data to include private firms in industry concentration measures and document a negative relation between industry concentration and multiple measures of voluntary disclosure, such as management earnings forecasts, analyst ratings, and analyst forecast properties. With their measure, they also show that the Harris (1998) results are no longer statistically significant and that the Verrecchia and Weber (2006) results reverse.

In addition to the difficulty of empirically capturing competition, the endogenous nature of competition also hinders researchers from causally identifying the impact of competition on disclosure (Huang et al. 2017). Given these empirical challenges, recent studies attempt to identify the impact of product market competition on disclosure with several unique settings. Using large tariff rate reduction events as quasi-exogenous shocks that increase product market competition, Huang et al. (2017) document a negative impact of the competition between existing rivals on management forecast issuance. By contrast, using the staggered adoption of the Interstate Banking and Branching Efficiency Act (IBBEA) to identify exogenous increases in the threats of potential entrants in the banking industry, Burks et al. (2018) find that incumbent banks issue more press releases after the adoption of IBBEA. Relatedly, a few studies test the proprietary cost hypothesis, though without focusing on the impact of competition. For examples, Li et al (2018) and Chatterjee, Gupta, and Kong (2020) provide evidence supporting the proprietary cost hypothesis by exploiting the staggered adoption of the inevitable disclosure doctrine across states and XBRL adoptions across firms, respectively.

In sum, the impact of product market competition on firms' disclosures remains an ongoing focus of debate, indicating that there probably exist other factors playing a role in this relation yet still unknown in the extant literature. Rather than trying to reconcile the conflicting findings, I attempt to provide novel insight into the impact of product market competition with existing rivals on firms' disclosure content relative to that of peer firms. The study complements the literature by providing a new perspective for understanding the competition-disclosure relation.

2.2. Product market competition and disclosure content difference

Though the proprietary cost hypothesis initially predicts the *quantity* of disclosures (Verrecchia 1983, 1990; Clinch and Verrecchia 1997), the discussion extends to the *quality* of disclosures, such as management forecast horizon and analyst ratings (Ali et al. 2014) and management forecast accuracy (Chatterjee et al. 2020). The intuition for such extension is that firms can reduce proprietary costs of disclosure by reducing the informativeness and/or increasing the noise of disclosure to rivals.

Firms cannot arbitrarily reduce the amount of information to disclose. Particularly in a setting of mandatory disclosure, though firms could make shorter disclosures or redact sensitive texts to protect proprietary information, they must disclose the minimum quantity of information required by regulators, which inevitably incurs proprietary costs. An alternative option to save proprietary costs is to increase the processing costs of disclosure (see Blankespoor et al. 2020 for a review),[3] as higher disclosure processing costs hinder information users from fully or quickly

[3] As is discussed in Blankespoor et al. (2020), firms can manage disclosure processing costs in various ways, including changing investor inattention, recognition versus disclosure, information overload, disclosure readability, and

understanding the disclosed information. Consistent with this view, Rahman et al. (2019) find a negative relation between product market competition and firm annual report readability.

The difference in disclosure content of a firm relative to that of its peers likely affects disclosure processing costs. The concept of disclosure content difference is related to the *comparability* of accounting information between peer firms. As the Financial Accounting Standards Board (1980) states, "comparability is the quality of information that enables users to identify similarities and differences between two sets of economic phenomena." Provided that industry peers face a similar economic environment, the extent to which the disclosure content difference between peer firms deviates from the difference in their fundamentals reflects the *incomparability* of the disclosed information between them. As accounting comparability improves the firm information environment (De Franco, Kothari, and Verdi 2011) and reduces processing costs (Blankespoor et al. 2020), higher disclosure topic difference, conditional on similar fundamentals, leads to higher disclosure processing costs.

Although the extant literature has examined various aspects of corporate disclosure, including both quantity and quality, these metrics of disclosure are by nature independent of other firms' disclosure behaviors. Firms, however, "do not exist as isolated islands" (Coase 1937). Prior studies have shown how a firm's disclosures can be influenced by and related to those of peer firms. For examples, peer firm disclosure can serve as a substitute for firm information to investors (Shroff et al. 2017) and can also help identify incomplete or unusual firm disclosure (Blankespoor 2019). Given the *interdependence* of disclosures between peer firms, it is surprising that very few studies have examined the extent to which a firm's decision on the content of disclosure may depend on those of peer firms. This paper attempts to capture such interdependence by creating a

accounting standard comparability.

measure of disclosure topic difference between peer firms.

I examine how a firm's disclosure topic difference varies in response to product market competition. As a *relative* metric of corporate disclosure, disclosure topic difference is particularly relevant in the setting of competition, as product market competition is a multiplayer game, where each player's strategy depends on all other players' strategies. Consequently, product market competition may affect not only the quantity and quality of a firm's disclosure independent of other firms' disclosure behaviors, but also the disclosure content relative to rival firms' disclosures. Furthermore, since higher disclosure topic difference likely increases disclosure processing costs, higher product market competition with existing rivals is expected to lead to higher topic difference between firms' disclosures, consistent with the proprietary cost hypothesis.

Psychological theory supports this prediction. Under the pressure of being held accountable, disclosers tend to adopt an evasive tactic to minimize accountability pressure (Green, Visser, and Tetlock 2000). To do so, disclosers discuss irrelevant or excessively general topics so that information receivers will allocate less attention to more important topics (e.g., Hurtig 1977; Harris 1991). When facing fierce competition, firms are under the accountability pressure from existing rivals and motivated not to reveal proprietary information. Hence, deviating from the topic set covered by peer firms helps distract information users' attention from topics of "common concern" and reduces the proprietary costs of disclosure. Formally, the hypothesis is stated below.

Hypothesis: Product market competition with existing rivals exhibits a positive impact on firms' disclosure topic difference relative to their industry peers.

However, larger disclosure topic difference might also be a result of the disclosure of new firm-specific information, or the difference per se might be interpreted as a signal by the market. In either case, higher disclosure topic difference might convey even more information than lower difference and therefore could be negatively associated with product market competition. Thus, the impact of product market competition on a firm's topic difference is not clear a priori.

2.3. MD&A disclosure

Disclosure in the MD&A section is appropriate for my analysis, as it is a form of mandatory disclosure that nonetheless reserves considerable content discretion for managers (e.g., Brown and Tucker 2011). The mandatory nature of MD&A provides the basis for a large-sample comparison across firms, while managerial discretion ensures both firm and time variability for comparison.

MD&As convey decision-useful information (e.g., Cole and Jones 2005; Feldman et al. 2010). Item 303 of Regulation S-K mandates that companies provide an MD&A as Item 7 in the 10-K filing. Managers are required to discuss in the MD&A (1) the results of operations and (2) liquidity and capital resources. Additional required topics include critical accounting policies and estimates, market risk disclosure, and off-balance sheet arrangements. The MD&A section allows investors to "see the company through the eyes of management," helping information users understand the reasons for changes in operating results and financial condition, and assess the implications of these changes for future cash flows (SEC 2003). More relatedly, the SEC also recommends that the MD&A section of a firm's 10-K include a discussion of the firm's competitive position (Exchange Act Release No 34-48960). The discretion accorded to managers allows them to tailor disclosure to suit each business (Brown and Tucker 2011).

Prior studies have taken various approaches to quantitatively analyzing disclosure in the MD&A: (1) hand-coded content analysis (Bryan 1997; Rogers and Grant 1997), (2) survey-based analysis (Clarkson, Kao, and Richardson 1999; Barron, Kile, and O'Keefe 1999), and (3) automated text analysis (e.g., Li 2008; Feldman et al. 2010; Muslu, Radhakrishnan, Subramanyam, and Lim 2015). Earlier hand-coded analyses provide important insights into the contents of

MD&A disclosures. However, the hand-coding approach is highly dependent on the researcher's discretionary judgment, leading to limited sample size and difficulties for replication. While free of researchers' bias, recent automated text analyses mostly focus only on the tone of the MD&A disclosure (e.g., Li 2008; Feldman et al. 2010; Muslu et al. 2015).

Despite the aforementioned studies, an important facet of MD&A disclosure has been largely unexplored: To what extent is the content of a firm's MD&A different from those of other firms? In a study more related to my own, Brown and Tucker (2011) compare the MD&A narratives in different years for the same firm and capture year-over-year MD&A modifications using the cosine similarity of the texts. Aiming to identify boilerplate disclosure, they therefore focus on the *word similarity* of MD&A disclosure. By contrast, I attempt to uncover topics underlying MD&A texts and compare the thematic content, rather than the wording, of MD&A disclosures. Moreover, I primarily make comparisons between rather than within firms.

3. Measuring the Topic Difference of a Firm's Disclosures from its Peers

3.1. The MD&A data

My MD&A sample period spans fiscal year 1994, the first year in which 10-Ks are widely available on EDGAR, through 2017, the last year for which the tariff rate data is available.[4] I download 10-K filings from the "Stage One 10-X Parse Data," generously provided by Bill McDonald on the Notre Dame Software Repository for Accounting and Finance (SRAF) website.[5]

[4] I use annual, rather than quarterly, data for several reasons: First, annual data avoid seasonality and Compustat's updates of originally reported quarterly data (Feldman et al. 2010); second, even firm-years with the same fiscal year end may have very different quarter ends, rendering quarterly data hardly comparable across firms; lastly, as is shown in Griffin (2003), the market reaction to 10-Ks is stronger than to 10-Qs.

[5] The 10-K filings are available at https://sraf.nd.edu/data/stage-one-10-x-parse-data/. The 10-K documents are texts after cleaning of extraneous materials, including HTML code, embedded PDF's, jpgs, and other artifacts not typically of interest for typical textual analysis. More detail about the cleaning process is discussed in Loughran and McDonald (2016).

I keep only 10-Ks for firm-years with tariff rate data available (i.e., SIC code in 0100-1499 and 2000-3999). Then I extract the MD&A text from Item 7 in each filing.

3.2. Modelling topic through Latent Dirichlet Allocation (LDA)

I model disclosure topic using LDA, a widely used unsupervised Bayesian machine-learning approach developed by Blei, Ng, and Jordan (2003) to identify the *topics* contained in a large corpus of text (see Appendix E for more information). LDA uses a statistical generative process to imitate the writing behavior of humans and exhibits strong performance in topic classification as compared to humans (e.g., Anaya 2011; Chang, Gerrish, Wang, Boyd-Graber, and Blei 2009). It uses the probability of words co-occurring within documents to identify a finite set of topics and their associated words. The researchers assign a label to the topic based on their assessment of the likely content given the set of words and their probabilities. To the extent that LDA reduces the dimensionality of the text data, it is conceptually similar to principal component analysis, where the LDA model produces topics instead of components.

LDA is particularly useful in my setting. It allows me to identify the mix of topics in the MD&A and, more importantly, compare the topics across different firm-years. Moreover, as an unsupervised method, the LDA is replicable and free of researchers' bias. Given its intuitive characteristics and strong performance, the LDA technique has been applied in accounting research. Using LDA to draw and compare topics covered in analyst reports and corporate disclosures, Huang et al. (2018) examines the information intermediary role of analysts. Dyer et al. (2017) use LDA to identify the topics that drive the evolution of 10-K text disclosure. Furthermore, Brown et al. (2020) explore the topics in 10-K narratives and predict financial misreporting using topic coverage.

While prior studies are interested in *categorizing* a financial text document into specific topics, my study focuses on *comparing* the difference of topics covered by different financial text documents (MD&As, in this case). This different research purpose leads to two major differences between my study and prior studies in the application of LDA: first, the interpretability of topics does not concern me much; second, the topics extracted from the corpus need to be sufficiently distinct from each other so that the topic difference between MD&As can be reliably measured.

Following Huang et al. (2018), I implement LDA by business sector because many topics are likely industry specific.[6] Based on the firms' SIC codes, I classify their 10-Ks into three industry groups: Agriculture, Forestry, and Fishing (SIC code between 0100 and 0999 inclusive); Mining (SIC code between 1000 and 1499 inclusive); and Manufacturing (SIC code between 2000 and 3999 inclusive). In each group, after tokenizing the MD&A text (i.e., converting the text into an array of words) and removing the stop words, I stem and lemmatize the words to their "root" form.[7] I keep in the corpus only words that appear in at least 10 documents but in less than 90 percent of documents, so that the words can better distinguish a MD&A document from others. On the flip side, doing so also likely excludes most common words and, subsequently, topics from the corpus.[8] Next, I apply the term frequency-inverse document frequency (tf-idf) technique, a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus (Rajaraman and Ullman 2011), to adjust the weight of each word in the corpus so that

[6] I am aware that Brown et al. (2020) apply LDA using a dynamic time-series process, since annual report content likely varies over time (Dyer et al. 2017). However, given that a firm typically issues only one 10-K per year, and that my sample only includes firms in a small number of industries that have tariff rate data available (i.e., SIC code in 0100-1499 and 2000-3999), I do not apply the dynamic time-series process of LDA, as the corpus for LDA training would be too small to produce reliable results.

[7] For grammatical reasons, documents may use different forms of a word, such as "organize," "organizes," and "organizing." Additionally, there are families of derivationally related words with similar meanings, such as "democracy," "democratic," and "democratization." The goal of both stemming and lemmatization is to return a word to its "root" form, so that words in different forms but with effectively the same meaning are considered by the machine as the same "token." Stemming reduces inflectional forms (e.g., return "organizes" to "organize"), while lemmatization simplify derivationally related forms of a word to a common base form (e.g., convert "democratically" and "democracy" to "democrat"). Note that the result from stemming and lemmatization may be an "incorrect" word in English language (e.g., "company" can be converted to "compani").

[8] All results are qualitatively similar if I relax the "10 documents, 90 percent" requirement.

more representative words gain higher importance in the corpus.

The total number of topics for each industry is set at 15 based on the analysis of the coherence score. This topic number is smaller than that used in prior studies (e.g., Huang et al. 2018; Dyer et al. 2017; and Brown et al. 2020), as I use only the MD&A section rather than the full 10-K filling. More importantly, the number of topics of the model affects the interpretability of the results (Huang et al. 2018): A smaller (larger) number can result in broader (narrower) and more ambiguous (specific) topics, but each topic is more (less) *distinguishable* from the others. Therefore, I set the number of topics to the lowest value that makes the coherence score sufficiently high, given my focus on the topic *difference* of a firm's disclosure (Rus, Niraula, and Banjade 2013).[9] I list the 5 topics with the highest frequency and the representative words for each topic in Appendix D.

3.3. Quantifying topic difference between MD&A documents

The output of LDA is an array of probabilities over a finite number of topics for each document, which add up to one. Following Rus et al. (2013), I capture the thematic topic difference between two MD&A using the Jenson-Shannon distance between the two corresponding topic vectors. The Jenson-Shannon distance is the square root of the Jenson-Shannon divergence, which measures the "dissimilarity" between probability distributions. The Jenson-Shannon distance is bounded between 0 and 1, with higher value representing a larger difference between two probability distributions. I multiply this distance by 100 as my empirical measure of topic difference.

Using this measure, I calculate the topic difference between MD&As from any two firm-years. For further analysis, I construct a topic difference measure of MD&A disclosure at the firm-

[9] In untabulated analyses, I alter the number of topics to 7, 10, and 20, respectively. All the findings discussed in this study are robust to these different specifications of the number of topics.

year level (*TopicDiff t*) by averaging the pairwise topic differences of a firm-year with all other MD&A disclosures in the same three-digit-SIC industry-year.

3.4. The trend of disclosure topic difference over time

Figure 1 shows the variation of topic difference of MD&A over time. The black line connects the mean topic difference values in each year, the blue belt shows the 95 percent confidence interval of the mean topic difference in each year, and the red dashed line marks the mean topic difference of all firm-years. The figure reveals a downward trend in the topic difference of MD&As between peer firms, whereas the cross-sectional variability of the topic difference is largely steady over time. This downward trend is consistent with Brown and Tucker (2011), who, using a cosine measure, find a decreasing trend in *textual* difference of MD&As between firms. Brown and Tucker (2011) interpret their finding as evidence that managers increasingly use boilerplate disclosure in MD&A. The trend in topic difference of the MD&As complements Brown and Tucker (2011) in that the higher textual similarity might well reflect the fact that firms are more prone to discuss similar topics, consistent with Dyer et al. (2017).

[*Insert Figure 1 Here*]

3.5. Validation of the measure of topic difference

Before conducting further analysis, I validate the measure of topic difference through a series of tests in Table 1. First, firms in the same industry and/or same year should disclose more similar topics than those that are not in the same industry and/or same year. Thus, in Panel A, I compare the pairwise topic difference from the same versus different three-digit SIC industries, years, and industry-years. For each group, I randomly draw 3,000 pairs of firm-years, and the results show that firm-years from the same industry (year) exhibit significantly lower topic difference in MD&A disclosure than those from different industries (years), with the lowest topic difference for those from the same industry-year.

[*Insert Table 1 Here*]

Further, as covered in section 2.3., managers are expected to discuss issues related to firm operations and liquidity and capital resources. Therefore, *ceteris paribus*, firms with similar fundamentals should cover similar topics in the MD&A. I test this prediction in Panel B by examining the relation between pairwise topic difference and the partial correlation of daily stock returns adjusted for market returns for the same pair of firms over the same fiscal year, a proxy for the fundamental similarities between firms. I randomly draw 10,000 firm-year pairs and dissect them based on partial correlations of stock returns, from low to high, into quartiles. The results show that firm-year pairs with higher (lower) return correlations, and therefore lower (higher) differences in fundamentals, exhibit lower (higher) topic difference in MD&A disclosure. That is, the measure of topic difference reflects the difference in firm fundamentals well.

Third, I explore the determinants of the firm-year-level disclosure topic difference. In addition to the negative association between a firm's disclosure topic difference ($TopicDiff_{t}$) and its fundamental similarity ($FundSim_{t}$) to industry peers, I also expect disclosure topic difference to be negatively associated with the length of MD&A section ($Length_{t}$), since lengthier disclosure likely covers more topics and therefore more likely covers the topics discussed by peer firms.[10]

To rule out potential confounding factors, I control for an array of variables that may be associated with disclosure topic difference, following prior disclosure literature (e.g., Ajinkya, Bhojraj, and Sengupta 2005; Baginski, Hassell, and Kimbrough 2002; Jennings, Seo, and Tanlu 2014). I include bond and equity issuance in the subsequent year ($Issue_{t+1}$), since firms may change

[10] The lengthier a pair of documents, the more probable a topic is to be included in both documents, leading to a lower likelihood that the documents will differ. This implies that the pairwise difference of a document is a decreasing function of the length of the document. I analytically prove this statement in the supplemental appendix.

their disclosure behaviors when raising capital. I add book-to-market ratio (*BM* $_{t-1}$), return on assets (*ROA* $_{t-1}$), firm size (*LnAsset* $_{t-1}$), leverage (*Leverage* $_{t-1}$), and sale growth (*SaleG* $_{t-1}$) to account for firm fundamentals that may affect a firm's disclosure behaviors. Stock return volatility (*RetVol* $_{t}$) captures the firm's overall risk, and annual stock return (*AnnRet* $_{t}$) controls for firm performance. I add the concentration index of the industry (*HHI* $_{t}$) to control for the potential influence of industry structure on disclosures. The firm's beta (*Beta* $_{t}$) captures its exposure to market risk. Analyst coverage (*AnaCov* $_{t}$) accounts for the firm's information environment. The number of geographic and business segments (*Segment* $_{t}$) proxies for firm complexity. The frequency of management forecast guidance (*GuideFreq* $_{t}$) and the number of 8-Ks issued (*Count8k* $_{t}$) during the fiscal year capture the voluntary disclosure behavior of the firm. Discretionary accruals (*DA* $_{t}$) measures the earnings reporting motives of the firm. Lastly, an indicator of credit rating (*Rated* $_{t}$) proxies for the firm's debt market incentives. Appendix A provides details of variable definitions.

Panel C reports the results. In both columns, the length of the MD&A (*Length* $_{t}$) and the fundamental similarity (*FundSim* $_{t}$) of a firm to its peers are negatively associated with disclosure topic difference, as expected. In column (2), a firm's disclosure topic difference is larger for firms with larger size (*LnAsset* $_{t-1}$), smaller book-to-market ratio (*BM* $_{t-1}$), better profitability (*ROA* $_{t-1}$), and smaller sales growth (*SaleG* $_{t-1}$). A firm is also likely to exhibit higher topic difference in its disclosure when the firm has more volatile stock return (*RetVol* $_{t}$) but smaller exposure to stock market risk (*Beta* $_{t}$), and when the firm is more complex (*Segment* $_{t}$). Interestingly, a firm that plans to raise capital in the subsequent year (*Issue* $_{t+1}$) is less likely to differentiate its disclosure contents from the peers. Firm-years that provide more voluntary disclosures (*Count8k* $_{t}$ and *GuideFreq* $_{t}$) are also more likely to have higher disclosure topic difference in the MD&A. Finally, it is particularly worth noting that topic difference is higher for firms in low-market-concentration

(*HHI* $_t$) industries, lending some initial support to my hypothesis of a positive relation between product market competition and disclosure topic difference, before more rigorous analyses.

Lastly, an important premise of further analyses is that high disclosure topic difference increases the processing cost of disclosure to product market competitors. Though establishing the causal link is difficult, I follow Blankspoor et al. (2020) and alternatively show in Panel D how disclosure topic difference is associated with several proxies of *investors'* and *analysts'* processing costs, including Amihud's (2002) illiquidity measure (*LnAIM* $_{t+1}$), stock return volatility (*RetVol* $_{t+1}$), analyst EPS forecast error (*FError* $_{t+1}$), and dispersion (*FDisp* $_{t+1}$) in the fiscal year following the disclosure. I find high topic difference to be associated with higher stock illiquidity, return volatility, and higher analyst forecast error, indicating that investors and analysts are likely less able to efficiently process the information disclosed by disclosers with higher topic difference.

Overall, the results confirm the topic difference of a firm's MD&A as a valid measure of the difference in the content of the firm's MD&A disclosure relative to those of its peers, and reveal that disclosure topic difference is positively associated with the processing costs of disclosure. I apply the firm-year measure of topic difference (*TopicDiff* $_t$) in further analyses.

4. Data and Identification

4.1. U.S. import tariff rates and product market competition

I exploit large tariff rate reductions as quasi-exogenous shocks that increase product market competition with *existing* foreign rivals, following a large line of literature (e.g., Frésard 2010; Valta 2012; Flammer 2015; and Huang et al. 2017). According to the vast literature on barriers to trade, the globalization of economic activities and international trade liberalization bring major changes in the competitive configuration of industries (see Tybout 2003 for a survey). In particular, the lessening of trade barriers triggers significant intensification of competitive pressures from foreign rivals (Bernard, Jensen, and Schott 2006). Valta (2012) reports that as tariff rates fell from about 3 percent to below 1.5 percent, import penetration rose from 19.5 percent to 24.1 percent, consistent with U.S. firms facing more competition from foreign firms. Xu (2012) documents a significant decrease in U.S. domestic firms' profit margins at both the industry and firm levels following large tariff rate reductions (see also, Katics and Petersen 1994). These results confirm large tariff reductions as events that exogenously shift the competitive landscape of industries.

I obtain U.S. import data for the period 1993 through 2017 from Peter Schott's website (see http://faculty.som.yale.edu/peterschott/) to compute the tariff rate for each industry-year (at the three-digit SIC level) as the duties collected at U.S. Customs divided by the Free-on-Board custom value of imports. Then I identify as the events all industry-years for which the tariff rate decreases relative to the previous year by more than three times the median tariff rate reduction during my sample period. To ensure that these large tariff rate reductions reflect non-transitory changes in the competitive environment, I exclude reductions that are preceded or followed by a tariff increase greater than 70 percent of the reduction. I identify 38 large tariff rate reduction events, and the treated industries are largely consistent with the prior literature.[11] Prior to the tariff reduction, all of these industries have a material amount of imports, indicating competition with existing foreign rivals. Appendix B presents the list of large tariff rate reduction events used in my final sample.

4.2. Data and sampling method

I start with the Compustat universe and collect annual financial statement data for fiscal years from 1994 to 2017. Given that the annual tariff rate record is on a calendar-year basis, I keep

[11] In untabulated tests, I replicate the tests in Huang et al. (2017) regarding management forecast frequency with my list of tariff reduction events. All the results are qualitatively similar, lending further confidence to the validity of my list of events. Furthermore, all my results are also qualitatively similar using the list of tariff reductions in Huang et al. (2017).

only firm-years with December as the fiscal year end month. Furthermore, only industries with import data available are included in my sample (i.e., SIC code in 0100-1499 and 2000-3999). I match firm financial data to tariff rate data using the three-digit SIC code.[12] Then I match the dataset of disclosure topic difference using Central Index Key and fiscal-year-end date. I collect control variables from IBES (analyst and management forecast variables), CRSP (stock returns and betas), and EDGAR (the number of 8-K filings). The final sample consists of 9,209 firm-year observations of 1,890 unique firms in 89 industries. Appendix C summarizes the sampling procedure. To mitigate the influence of extreme values on my results, I winsorize all continuous variables at the 1 percent and 99 percent levels.

I present summary statistics in Table 2. Panel A shows the descriptive statistics for the variables in my sample and the differences in the variables between the treated and control groups. Panel B reports the Pearson correlations between the variables.

[*Insert Table 2 Here*]

The number of treated and control firms are roughly balanced, with 4,182 firm-year observations being treated and 5,027 observations being control. Within treated firms, approximately 81 percent of the observations are in the post-reduction period. The post-reduction sample is larger than the pre-reduction sample, since most large tariff rate reduction events occur in early years, but EDGAR gradually has better coverage and data quality in more recent years.[13]

[12] Compustat only provides the most recent SIC of a firm, and the records for historical SIC are missing for many firms, potentially biasing my results, as firms may have changed industry during the period of analysis. Indeed, between 1994 and 2017, over 6,500 firms changed their SIC code. That is, on average, more than 250 firms in the Compustat universe change their SIC industry every year. As such, I use the SIC documented in the 10-K filing to identify the industry of the corresponding firm-year.

[13] The average U.S. tariff decreased by about 75 percent, from 8.23 percent in 1974 to 2.15 percent in 2005 (Frésard and Valta 2016), leaving limited room for further reductions thereafter. Indeed, the most recent wave of tariff reductions in the United States is primarily the result of bilateral and multilateral trade agreements with the 1994 North American Free Trade Agreement (NAFTA). More recent years, however, have witnessed several trade conflicts between the United States and other countries that mark the slowdown in the process of trade liberation. Meanwhile, the EDGAR has had much better coverage since 1996, and the data quality has also become better over time, leading a larger proportion of the sample to be firm-year observations in more recent years.

Relative to the control firms, firms in industries hit by large tariff rate reduction events exhibit higher topic difference in MD&A disclosure relative to industry peers, consistent with my hypothesis. In the meantime, treated firms also tend to be fundamentally less similar to their peers and to have shorter MD&A disclosure. In addition, treated firms tend to be smaller but more profitable than control firms and to have lower sales growth, smaller exposure to systematic risks in the stock market, and less discretionary accruals. Treated firms also tend to issue more management forecasts and are more likely members of industries with higher concentration, but less likely to have a credit rating.

4.3. Identification strategy

To identify the impact of product market competition on disclosure topic difference, I employ a diff-in-diff technique through an OLS regression relating disclosure topic difference to large import tariff rate reduction events, as stated in equation (1).

$$TopicDiff_t = \beta_0 + \beta_1 PostDrop_t + Controls + Firm\ FE + Year\ FE + \varepsilon_t \qquad (1)$$

A positive value of β_1, the diff-in-diff coefficient, would indicate a positive impact of large tariff rate reduction events ($PostDrop_t$) on disclosure topic difference ($TopicDiff_t$). I add into the model all independent variables used in the validation test discussed in section 3.5 (presented in Column (2) of Table 1 Panel C) as controls. Notably, since I focus on a firm-specific response to industry-wide common shocks, it is necessary to rule out potential confounding effects due to intra-industry differences across firms. Therefore, to apply this generalized diff-in-diff model, I include firm-, rather than industry- (as in Table 1 Panel C), fixed effects and year-fixed effects to control for unobservable factors, over time and across firms, that may affect firms' disclosure topic difference.

5. Empirical Results

5.1. The impact of large tariff rate reductions on disclosure topic difference

Table 3 reports the estimation results for the impact of large tariff rate reductions on firms' disclosure topic difference of MD&As (equation (1)). Column (1) presents the results without including the control variables, while column (2) adds the firm's fundamental similarity with its peers and the length of the MD&A, which are the two most relevant control variables according to the results in the validation test; column (3) includes all control variables. I cluster the estimated standard errors at the firm level to address potential heteroskedasticity.

[*Insert Table 3 Here*]

Through all three columns, I find positive and statistically significant diff-in-diff coefficients, ranging from 3.9196 to 4.6820. That is, an average firm differentiates the thematic contents of its disclosure by approximately 28 percent of the standard deviation in response to a large tariff reduction. The results for the control variables are consistent with those in Table 1.[14]

5.2. The magnitude of tariff reduction and competition-induced disclosure differentiation

If the increase in firms' disclosure topic difference is indeed *caused* by an increase in competition following tariff reduction events, the impact should be more pronounced when the reductions result in a greater increase in imports, as a larger increase in imports means a larger increase in competition from foreign rivals. Furthermore, if the increase in competition comes mainly from existing foreign rivals, then the impact of tariff rate reductions on disclosure topic difference should be greater for industries with more imports prior to the tariff reduction.

Table 4 Panel A compares the impact of tariff reductions on disclosure topic difference in industries with small versus large increases in imports after tariff rate reduction events. I dissect

[14] In untabulated analyses, all my results are qualitatively similar when I control for industry-fixed effects (at the three-digit SIC level) instead of firm-fixed effects.

treated industries into two groups with small versus large increases in imports by the change of import value in the event year. I am unable to rank control industries, so I include them in the tests for both the large- and small-import-increase groups. On average, a tariff rate reduction leads to an increase in disclosure topic difference by 20 (34) percent of the standard deviation in industries with small (large) import increases. The impact is statistically different between the two groups.

In Panel B, I perform a similar test conditional on the pre-reduction level of imports. I rank treated industries based on the ratio of imports to the sum of sales of all firms in the industry in the year preceding the tariff-reduction year, and dissect them into low- versus high-pre-reduction-import groups. The coefficient on $PostDrop_t$ is statistically insignificant in the groups with low pre-reduction imports, but positive and statistically significant in the high-pre-reduction-import group. The difference in the impact between the two groups is also statistically significant.

[*Insert Table 4 Here*]

Overall, the results suggest that the impact of tariff rate reductions on disclosure topic difference is stronger when the tariff reduction likely exhibits larger influence on the competitive landscape of the industry, lending further support to tariff rate reductions as a *cause* of disclosure topic differentiation.

5.3. Proprietary costs and competition-induced disclosure topic differentiation

I posit that the increase in topic difference following tariff reductions is due to proprietary-cost concerns. If this conjecture is correct, then I expect the increase to be greater when the disclosure is associated with higher proprietary costs. However, directly measuring the proprietary costs of disclosure is difficult. Prior research suggests that the proprietary costs of disclosure increase in the profitability of the firm (Berger and Hann 2003) and the amount of information disclosed about industry demand (Clinch and Verrecchia 1997).

Based on these findings, Table 4 Panel C dissects all firm-years into two groups, small versus large profit margins, using industry-median return-on-assets. The coefficients on *PostDrop* are statistically significant in both groups but much larger in the large-profit-margin group than in the small-profit-margin group. The between-group difference in the impact is statistically significant. Furthermore, to the extent that disclosure from firms with larger market shares likely contains more information on industry demand, a firm's market share proxies the amount of industry demand information in its disclosure (Huang et al. 2017). Accordingly, Panel D partitions the sample into high versus low market share by its industry-median values. A significantly more positive coefficient on *PostDrop* in the high-market-share group indicates that firms whose disclosure more likely reveals information about industry demand are more likely to differentiate their disclosure from that of their peers. Taken together, the results strongly suggest that proprietary costs likely explain the impact of product market competition with existing rivals on disclosure differentiation.

5.4. Fundamental similarity and competition-induced disclosure topic differentiation

A firm with more similar fundamentals to its industry peers is also likely facing more competitive pressure from the peers. Therefore, if competition with existing rivals is the reason for disclosure differentiation, I expect the impact of tariff reductions on disclosure topic difference to be more pronounced in firms with more similar fundamentals to their peers. In Panel E of Table 4, I partition the sample into low versus high fundamental similarity to industry peers by the sample-median value. Tariff reductions lead to an increase in disclosure topic difference by 22 (39) percent of the standard deviation in firms with low (high) fundamental similarity, and the difference between groups is statistically significant, consistent with my prediction. Thus, the competition with existing rivals is a plausible *cause* of disclosure differentiation.

5.5. Disclosure length and competition-induced disclosure topic differentiation

Longer disclosure likely contains more information than shorter disclosure, leading to larger concerns about proprietary costs. Therefore, shortening disclosure can be an option for firms seeking to protect proprietary information. However, given that firms are *required* to disclose certain information in the MD&A, this option is not always feasible. In this case, content differentiation is a potential substitute for shorter disclosure in withholding proprietary information. Hence, I predict the impact of product market competition to be stronger for firm-years with longer MD&A disclosure. Panel F of Table 4 partitions the sample into short versus long MD&A disclosure by the sample-median length of MD&As. The impact of tariff reduction events is positive and statistically significant only in firms with relatively long MD&A disclosure, and the between-group difference is also statistically significant, consistent with the proprietary cost hypothesis. The results also lend support to the conjecture that disclosure differentiation can be a substitute for shorter disclosure in protecting proprietary information.

6. Additional Analyses

6.1. Propensity score matching

Though tariff reduction events are plausibly exogenous, it is hard to rule out the possibility that firms could self-select to either join or leave an industry. Furthermore, the sample period (1994 – 2017) in my main analysis is long, and some time-varying factors may therefore confound my findings. For instance, it is possible that the tariff reduction event in an industry reflects specific forces within the industry, which could lead to further policy changes in the same direction. I address these concerns by conducting the tests in a propensity-score-matched sample within a 11-year window centered at the tariff reduction event year. I expect that firms are more likely to change industry if they are smaller, more leveraged, and have lower book-to-market ratios because they are likely more flexible in operation and more vulnerable to fierce competition. Thus, I estimate in the first stage the probability of being a member of a treated industry using firm size ($LnAsset_{t-1}$), financial leverage ($Leverage_{t-1}$), and book-to-market ratio (BM_{t-1}). Then I match, without replacement, each treatment firm in the year immediately preceding the tariff reduction event year to up to three control firms with the closest propensity score in same year and the same Fama-French-12 industry. In addition, I require both treated and control firms to have at least one observation before and one observation after the event. Table 5 presents the estimation results using a matched sample of 1,210 firm-year observations. I continue to document a positive and statistically significant impact of product market competition on disclosure differentiation. As such, I am confident that my main findings are robust to firms' self-selection on industry membership.

[*Insert Table 5 Here*]

6.2. The parallel trend assumption

A key presumption for the validity of the diff-in-diff approach is known as the parallel trend assumption. To check this assumption, I perform two robustness tests. First, I perform a placebo test in the full sample, where I force the tariff reductions to three years before the actual events. Second, I investigate the dynamic of the impact of tariff reductions on disclosure topic difference in the propensity-score matched sample.

[*Insert Table 6 Here*]

Table 6 Panel A reports the results of the placebo test. The counter-factual events of tariff reductions do not exhibit an impact on disclosure topic difference, indicating no evidence of a pre-event trend. Furthermore, Panel B shows that the impact of tariff reductions on disclosure topic difference manifests itself only in years after the event, further confirming the causal inference.

6.3. Consequences of disclosure differentiation in response to competition

The proprietary costs of disclosure imply that firms that are less able than their competitors to protect proprietary information are more likely to fall into a disadvantageous situation in the competition. Thus, if disclosure differentiation helps firms protect proprietary information and defend their competitiveness, a differentiating firm should gain an advantage in competition against its non-differentiating rivals. Table 7 tests this prediction by assessing whether higher disclosure topic difference improves the future performance of firms hit by tariff reductions *relative* to their low-topic-difference rivals. Since intense competition can impair the overall performance of all members in an industry, I capture a firm's *relative* future performance using its percentile within the three-digit-SIC industry, including the market share ($Rank\_Sale_{t+1}$), return-to-assets ($Rank\_ROA_{t+1}$), and Tobin's Q ($Rank\_Q_{t+1}$), measured in the year immediately following the disclosure.

[*Insert Table 7 Here*]

Column (1) shows that although tariff reduction events have a negative impact on firms' market share relative to that of their peers, those with higher topic difference partially undo this negative impact. Column (2) reports similar results for return-on-assets: higher topic difference in response to tariff reductions mitigates the negative influence of competition on a firm's relative profitability. Taken together, the results suggest that competition-induced disclosure differentiation helps firms defend their competitiveness in the product market.

By contrast, in column (3), competition-induced topic differentiation exhibits no impact on a firm's relative future Tobin's Q.[15] That is, investors do not seem to value disclosure-

[15] Note that because I control for firm fixed effects, I do not include lagged return-on-assets (ROA_{t-1}) as a control for the test of relative profitability because, econometrically, adding it to the regression may cause an estimation bias. For the same reason, I do not control for book-to-market ratio (BM_{t-1}) in the test of relative Tobin's Q, as the book-to-market ratio is effectively the same construct as Tobin's Q. Though potentially biased, the results are consistent when

differentiating firms higher than their non-differentiating counterparts.[16] The insignificant impact on firm value should be interpreted with caution. A possible explanation is that investors do not fully incorporate the positive influence of competition-induced disclosure differentiation into firm valuation, indicating that disclosure differentiation probably hinders investors from understanding the firm's prospects. An alternative explanation does not assume the naivety of investors. Firm value is a function of many different factors, and disclosure behavior may influence not only future cash flow but also firm cost of capital (e.g., Francis et al. 2008). Even though competition-induced disclosure differentiation leads to better future performance, it may, on the other hand, increase the information asymmetry between the firm and its investors due to an increase in the processing costs of disclosure, leading to a higher risk premium that cancels the positive cash-flow effect on firm value. In either case, the insignificant impact of competition-induced disclosure differentiation on firm value is consistent with an increase in disclosure processing costs.

In sum, the analyses reveal that although higher disclosure topic difference helps firms protect their proprietary information and defend their competitiveness in increased product market competition, investors do not value the contribution of such a strategy. Overall, the finding is consistent with the conjecture that higher disclosure topic difference increases the processing costs of the disclosure, validating topic difference as a method to save proprietary costs of disclosure.

6.4. Is disclosure differentiation a signal of firm prospects?

So far, I have drawn inferences based on the premise that the difference in a firm's disclosure topics relative to its industry peers is unassociated with *real* changes in firm activities.

I include lagged return-on-assets and lagged book-to-market ratio as controls in both tests.

[16] It is possible that differentiating firms are those already with extreme (either highest or lowest) Tobin's Q *values* in the industry before tariff reductions, so that no influence on the *percentile* of Tobin's will be detected. Thus, in an untabulated test, I also examine the influence of disclosure differentiation in response to competition on the value of firms' Tobin's Q, and I continue to find no statistically significant result.

Nonetheless, a firm may well differentiate itself from rival firms by changing its products, pricing strategies, or marketing activities. An alternative explanation could be that higher disclosure topic difference signals a firm's ongoing or future real changes in its fundamentals. To examine this possibility, I perform a path analysis, where I allow tariff reductions to indirectly affect a firm's disclosure topic difference through the concurrent and future fundamental similarity to peer firms.

[*Insert Figure 2 Here*]

Figure 2 presents the results from the path analysis. In the analysis, for the sake of simplicity, I also control for all other control variables in Equation (1) without reporting the results in the figure. The total effect of tariff reductions on disclosure topic difference is, in effect, exclusively explained by the direct impact. Tariff reductions reduce a treated firm's fundamental similarity to its peers, indicating that firms attempt to differentiate themselves from peers through changes in real activities. However, such "real" changes do not exhibit *incremental* explanatory power on topic difference. In other words, topic differentiation is unlikely a tool for managers to signal changes in either concurrent or future firm fundamentals.

6.5. Does the stock market react to competition-induced disclosure topic differentiation?

While high competition-induced disclosure topic differentiation does not seem to signal changes in firm fundamentals, it remains an open question whether and how investors interpret such topic differentiation at the time of disclosure. On the one hand, the differentiation in the MD&A disclosure may increase the processing costs of information, hindering investors from understanding firm operations, leading to no or even negative market reaction. On the other hand, investors might perceive differentiated disclosure as a positive message that the firm's business is less likely to be affected by the tariff reduction and therefore react in a positive manner. Thus, I investigate the short-window market reaction to differentiated disclosure following tariff reduction events by testing the cumulative abnormal return (*CAR*) in a window from 1 day before to 5 days after the 10-K filing date, when MD&A disclosure becomes available to investors.

[*Insert Table 8 Here*]

Table 8 reports the results for the short-window market reaction to disclosure topic difference. I obtain the CAR using Fama-French three-factor model (Fama and French 1993) with a 100-day estimation window.[17] I vary the control variables in column (1) through (3), and find no evidence that disclosure differentiation following tariff reductions affects the firm's filing returns, indicating that investors do not react to competition-induced disclosure difference. In other words, disclosure differentiation is very unlikely to be a signaling tool. Moreover, this result is also consistent with disclosure topic differentiation increasing the processing costs of disclosure.

7. Concluding Remarks

The effect of product market competition on managerial disclosure has been debated for decades in the accounting literature. This study attempts to provide novel insights to this discussion from the perspective of the thematic topics of MD&A disclosure in 10-K filings. I extract topics of an MD&A using LDA and quantify a firm's disclosure topic difference relative to its peers using Jenson-Shannon Divergence, derived from information theory (Rus et al. 2013). Exploiting U.S. import tariff rate reductions as quasi-exogenous shocks to product market competition with existing rivals, I employ a diff-in-diff technique and document a positive impact of competition with existing rivals on corporate disclosure topic difference. To the extent that higher disclosure topic difference increases the processing costs of the disclosure, the results suggest that firms differentiate their disclosure content from that of peers to protect their proprietary information in

[17] In untabulated analyses, my results are robust to different methods or different event windows to calculate CARs.

response to higher product market competition. The impact is more pronounced for firms whose competition environment is more likely reshaped by tariff reductions, those with likely higher proprietary costs, those fundamentally more similar to their peers, and those with lengthier disclosure. These results indicate that proprietary costs are likely driving the findings. My results are robust to a propensity-score-matched sample, and the parallel trend assumption also holds for the diff-in-diff analysis.

I further document that disclosure-differentiating firms, following increases in competition, exhibit better future performance in market shares and profitability relative to their peers. This suggests that higher disclosure topic difference helps to protect proprietary costs and defend competitiveness in the product market. However, the stock market does not seem to value such a strategy, consistent with high disclosure topic difference increasing information processing costs. Accordingly, firms also do not seem to use higher disclosure topic difference as a tool to signal differentiative changes in firm fundamentals relative to their peers.

Overall, I posit and find that firms differentiate their disclosure content from their rivals in response to an increase in product market competition so as to reduce the proprietary costs of disclosure and defend their competitiveness against their rivals in the product market. This study not only adds new evidence to the ongoing discussion regarding the relation between product market competition and disclosure, but also provides a novel dimension for understanding corporate disclosure behaviors with new techniques. My study may also be of interest to investors, as the stock market does not seem to take into valuation the fact that disclosure-differentiating firms tend to outperform their peers in the product market.

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Appendix A. Variable Definitions

Variable	Definition	Data Source
TopicDiff $_t$	Disclosure topic difference between two firms, defined as the Jensen-Shannon distance between two topic vectors generated by the Latent Dirichlet Allocation algorithm of two MD&A sections in two 10-K files issued by firms in the same 3-digit industry and in the same year.	EDGAR
Explanatory Variables		
PostDrop $_t$	Indicator for tariff rate drop, =1 if the firm's 3-digit SIC industry has experienced a large tariff reduction until year t, and =0 otherwise.	Peter Schott's Website
FundSim $_t$	The average partial correlation between the firm's monthly stock return and the monthly stock return of other firms in the same industry in year t, after controlling for market return.	CRSP
Length $_t$	The length of the MD&A section in the firm's 10-K in year t, measured as the number of bytes used to store the string of a MD&A section with utf-8 encoding.	EDGAR
Issue $_{t+1}$	Indicator of debt or equity issuance, =1 if the amount of net bond and equity issuance in year t is above zero, and =0 otherwise. Net bond and equity issuance is measured as ((dltis-dltr+dlcch)+(sstk-prstkc))/at.	Compustat
BM $_{t-1}$	Book-to-market ratio, measured as the book value of common equity (ceq) divided by the market value of common equity (prcc_f*csho)	Compustat
ROA $_{t-1}$	Return-on-assets of the preceding year, defined as net income (ni) of year t-1 scaled by total assets (at) at the beginning of year t-1.	Compustat
LnAsset $_{t-1}$	The natural logarithm of total assets (at) at the beginning of year t.	Compustat
Leverage $_{t-1}$	Financial leverage, defined as total debt (long-term debt plus debt in current liabilities) divided by total assets ((dlt+dlcc)/at) at the beginning of year t-1.	Compustat
SaleG $_{t-1}$	Sales growth in year t-1, defined as defined as the change in sales (Δsale) deflated by lagged sales (sale).	Compustat
RetVol $_t$	Annual stock return volatility, calculated by firm daily stock return in fiscal year t.	CRSP
AnnRet $_t$	Annual stock return of the firm in year t, calculated using monthly stock return.	CRSP
HHI $_t$	Industry concentration, defined as the Herfindahl-Hirschman Index of sales (sale) in the industry.	Compustat
Beta $_t$	Equity beta of the firm for the previous fiscal year.	CRSP
AnaCov $_t$	Analyst coverage, defined as natural logarithm of 1+the number of analysts following the firm at year t.	IBES, Compustat
Segment $_t$	Number of business and geographic segments, set to zero for missing values.	Compustat
GuideFreq $_t$	Management earnings forecast frequency of the firm in year t, defined as the number of management earnings forecasts issued in year t.	IBES Guidance
Count8K $_t$	The number of 8-K forms filed of the firm in year t.	EDGAR

DA_t	Discretionary accruals calculated as the residual from estimating the following modified Jones model within an industry for each year: $$\frac{TA_t}{A_{t-1}} = \alpha_1 \frac{1}{A_{t-1}} + \alpha_2 \frac{REV_t}{A_{t-1}} + \alpha_2 \frac{PPE_t}{A_{t-1}} + \varepsilon_t$$ where *TA* is total accruals ($\Delta\text{act} - \Delta\text{lct} - \Delta\text{che} + \Delta\text{dlc} - \text{dp}$), *A* is total assets (at), *REV* is sales revenue (sale), and *PPE* is gross property, plant, and equipment (ppegt).	Compustat
$Rated_t$	Indicator for credit rating, =1 if the firm has a credit rating available, and =0 otherwise.	Compustat
$SaleG_t$	Sales growth, defined as sales (sale) of year t minus sales in the preceding year scaled by sales in the preceding year.	Compustat
Variables Used in Validation and Additional Analyses		
$NPeer_t$	Number of industry peers, measured as the number of firms in the same 3-digit-SIC in the industry minus 1 in year t.	Compustat
$M2B_t$	Market-to-book ratio, measured as the market value of firm assets (prcc_f*csho+at-ceq) in year t divided by book value of total assets (at) in year t.	Compustat
$LnMV_t$	The natural logarithm of one plus market value of equity (prcc_f*csho) in year t.	Compustat
$LnAIM_{t+1}$	The natural log of one plus the yearly average of Amihud's (2002) illiquidity measure (AIM) in year t+1. AIM is calculated for each day in a fiscal year as the ratio of absolute stock return to dollar volume (10,000,000×|ret|/(prc*vol)). I then average these daily AIM over the fiscal year and take logarithms.	CRSP
$FError_{t+1}$	Analyst forecast error for the firm in year t, measured as the average of analyst EPS forecast error of the final forecasts from every analyst issued within the fiscal year t+1, where analyst forecast error is measured as the absolute difference between the forecast value and the actual value scaled by assets per share at the beginning of the year.	IBES
$FDisp_{t+1}$	Analyst forecast dispersion for the firm in year t, measured as the standard deviation of analyst EPS forecast value of the final forecasts from every analyst issued within the fiscal year t+1, where analyst forecast error is measured as the absolute difference between the forecast value and the actual value scaled by assets per share at the beginning of the year.	IBES
$Rank\_Sale_{t+1}$	The percentile of a firm's sales (sale) in the 3-digit SIC industry in year t+1.	Compustat
$Rank\_ROA_{t+1}$	The percentile of a firm's return-on-assets in the 3-digit SIC industry in the next year. Return-on-assets is defined as net income (ni) in year t+1 scaled by total assets (at) at the beginning in year t+1.	Compustat
$Rank\_Q_{t+1}$	The percentile of a firm's market-to-book ratio in the 3-digit SIC industry in the next year. Market-to-book ratio is measured as the market value of firm assets (prcc_f*csho+at-ceq) in year t+1 divided by book value of total assets (at) in year t+1.	Compustat

RD_{t-1}	R&D expenditure, defined as R&D expenditure divided by total assets (xrd/at) at the beginning of year t-1, set to zero for missing values.	Compustat
$CAR(-1,5)_t$	The cumulative abnormal return from 1 trading day before to 5 trading days after the 10-K filing date for fiscal year t.	CRSP

Appendix B. List of Industries with Large Tariff Rate Reductions

This appendix lists the 27 industries with large tariff rate reductions in the sample.

3-digit SIC industry	Year	Number of observations
131	1999	753
208	1999	129
243	2002	4
245	2017	46
284	1995	96
302	2004	7
306	1995	34
308	1997	173
327	1999	13
329	1996	15
342	1995	78
343	1997	10
345	1998	5
349	1995	49
353	1995	157
356	1995	204
357	1996	368
358	1997	93
359	1996	26
362	1996	70
363	1996	36
366	1995	387
369	1996	89
372	1998	107
381	1996	22
382	1996	501
384	1996	768

Appendix C. Sample Selection

This appendix details the sample selection method used to obtain the sample used in main analyses.

Total firm-year observations in Compustat from 1994 to 2017		266,474
Less		
Firm-years with fiscal year end month other than December	(75,890)	
Firm-years from industries without tariff rate data available (SIC 1500-1999 and 4000-9999)	(130,779)	
Firm-years not matched to EDGAR 10-K records	(24,258)	
Firm-years with missing value of disclosure topic difference	(19,235)	
Industries without a trackable record of tariff rate	(4,446)	
Firm-years with missing value of explanatory variables	(2,657)	
Final observations		9,209

Appendix D. Most Frequent Topics and Representative Words for Each Topic

This appendix presents the 5 most frequent topics and representative words for each topic for mining and manufacturing industries in the sample.

Panel A. Mining Industries

#Topic	Words
Topic #4	percent, sfas (Statements of Financial Accounting Standards), decreas, stage, share, increas, consolid, price, compar, natur
Topic #7	partnership, partner, decreas, overview, price, percent, product, barrel, distribut, qualt, quantit
Topic #15	enex (Enex Resources Ltd.), distribut, stage, atlas, percent, product, mine
Topic #9	miner, mine, stage, explor, fiscal, atlas, share, statement, compar
Topic #3	share, statement, currenc, quantit, mine, forward, critic, teminolog, common, risk

Panel B. Manufacturing Industries

#Topic	Words
Topic #15	product, revenue, research, clinic, expens, custom, develop, warrant, asset, cost, segment
Topic #9	ethanol, biodiesel, exhibit, product, breweri, foreign, compar, incorpor
Topic #6	incorpor, refer, caption, quantit, stockhold, inform, sharehold, analysi, disclosur, risk, fiscal, report
Topic #2	fiscal, increas, currenc, revenue, compar, foreign, sfas (Statements of Financial Accounting Standards), decreas, softwar, expens, percent, incom
Topic #12	head, independ, consild, auditor, fiscal, statement, index, tire, regist, segment, note

Appendix E. Topic Modelling and Topic Difference

This appendix provides a simple introduction to topic modelling, Latent Dirichlet Allocation, and topic difference. More detailed discussion on topic modelling, Latent Dirichlet Allocation, and applications to accounting research can be found in Huang et al. (2018), Dyer et al. (2017), and Brown et al. (2020). The supplemental appendix of this paper also discusses the techniques and the implementation in this study in greater detail.

Topic modelling is an approach to extracting thematic topics from a corpus of texts. A text document may contain several topics, where each likely has several particular words that appear in higher frequency. For example, words like “dog” and “bone” will appear more frequently in documents about dogs, while “cat” and “meow” will appear in documents about cats, and “the” or “is” will appear in both documents with a similar frequency. In this sense, a document can be viewed as a statistical mixture of topics, and a topic as a statistical mixture of words. A topic model captures this intuition in a mathematical framework, which allows the examination of a set of documents and a determination of what the topics might be and what each document’s balance of topics is, based on the statistics of the words in each topic.

LDA, developed by Blei, Ng, and Jordan (2003), is arguably the most widely used algorithm in topic modelling. LDA assumes that a document is generated by repeating two steps. First, a topic is randomly based on the topic distribution of this document; next, a word is randomly drawn based on the word distribution of the topic selected in the previous step. The two-step model essentially simulates a human’s writing behavior. Based on a set of statistical assumptions on the generative process, LDA is capable of mathematically solving for the parameters for the process using textual data and discovering the topics covered by each text document. To implement LDA, the research needs to specify the number of topics as an input parameter.

The output of the LDA model is a topic vector for each text document, which represents the probability distribution of the document over a finite set of topics. The values of all factors in the vector sum up to one. Though the vector resembles the coordinate of a point in a finite-dimensional space, one cannot measure the difference between two topic vectors using geometric tools such as distance (e.g., Euclidean distance) and degree of arc (e.g., cosine), because these vectors are essentially probability distributions. Information theorists build tools based on information entropy to measure the difference between two probability distributions, and the Jensen-Shannon divergence, among others, is one of the most popular measures. The Jensen-Shannon divergence is bounded between 0 and 1, with a larger value indicating a greater difference between two probability distributions. This study uses the square root of the Jensen-Shannon divergence, which is often referred to as the "Jensen-Shannon distance," between two topic vectors as the measure of difference between two topic vectors.

More detailed discussions regarding the methodology and data processing are available in the supplemental appendix of this study.

Table 1. The Validity of the Measurement of Topic Difference

This table presents the results of a series of validity checks of the measurement of disclosure topic difference. Panel A compares the disclosure topic differences between different groups of firm-year pairs; Panel B relates pairwise disclosure topic difference between firm pairs from the same industry in the same year to their pairwise stock return correlation; Panel C reports the results for regressions relating disclosure topic difference to an array of potential determinants. Panel D reports the results for regressions relating various proxies for disclosure processing costs to disclosure topic difference. All variables are defined in the Appendix A; all continuous variables are winsorized at their 1st and 99th percentiles; and t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Topic Differences between Different Groups

	Same industry *(N=3,000)*	**Different industries** *(N=3,000)*	**Same year** *(N=3,000)*	**Different years** *(N=3,000)*	**Same industry-year** *(N=3,000)*	**Different industry-years** *(N=3,000)*
Mean	52.291	58.390	56.879	58.333	50.902	56.971
(Std. Err.)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Difference	-6.099***		-1.454**		-6.069***	
(t-stat)	(10.222)		(2.455)		(10.178)	

Panel B. Topic Differences and Return Correlations

Return Correlation		**Quartile 1** *(N=2,500)*	**Quartile 2** *(N=2,500)*	**Quartile 3** *(N=2,500)*	**Quartile 4** *(N=2,500)*
Topic Differences	Mean	0.066	0.063	0.053	0.054
	(Std. Dev.)	(0.088)	(0.090)	(0.089)	(0.093)
$Q1 > Q2?$		$Q1 - Q2 = 0.003^{*}, \mathrm{P-value} = 0.091$			
$Q2 > Q3?$		$Q2 - Q3 = 0.010^{***}, \mathrm{P-value} = 0.000$			
$Q3 > Q4?$		$Q3 - Q4 = -0.001, \mathrm{P-value} = 0.724$			

Panel C. The Determinants of Topic Differences

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
$FundSim_t$	-1.6253***	-2.4455***
	(-4.59)	(-7.30)
$Length_t$	-0.0002***	-0.0002***
	(-29.08)	(-35.82)
$Issue_{t+1}$		-0.7166***
		(-2.65)
BM_{t-1}		-0.7163***
		(-4.05)
ROA_{t-1}		1.7570***
		(3.87)
$LnAsset_{t-1}$		1.7515***
		(14.02)
$Leverage_{t-1}$		-0.8109
		(-1.59)
$SaleG_{t-1}$		-0.3493***

		(-3.94)
RetVol $_t$		33.7760***
		(4.56)
AnnRet $_t$		0.1667
		(1.09)
HHI $_t$		-2.6599**
		(-2.35)
Beta $_t$		-0.5137***
		(-2.63)
AnaCov $_t$		0.0238
		(1.16)
Segment $_t$		0.4003***
		(4.27)
GuideFreq $_t$		0.3003***
		(3.60)
Count8k $_t$		0.1067***
		(4.30)
DA $_t$		-0.0290
		(-0.63)
Rated $_t$		0.2606
		(0.70)
Intercept	56.0257***	47.3903***
	(23.65)	(20.81)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adj.-R^2	0.4434	0.5161
N	9,209	9,209

Panel D. Topic Differences and Processing Cost

Dependent variables:	*LnAIM* $_{t+1}$	*RetVol* $_{t+1}$	*FError* $_{t+1}$	*FDisp* $_{t+1}$
	(1)	(2)	(3)	(4)
TopicDiff $_t$	0.0025***	0.0000*	0.0018*	0.0003
	(2.59)	(1.67)	(1.65)	(0.44)
Length $_t$	0.0000***	0.0000***	0.0000*	0.0000
	(4.73)	(4.02)	(1.77)	(1.07)
FundSim $_t$	-0.0452**	0.0012***	0.0242	0.0112
	(-1.98)	(2.64)	(0.82)	(0.73)
NPeer $_t$	0.0008***	0.0000***	0.0011*	0.0007*
	(2.59)	(3.08)	(1.70)	(1.72)
M2B $_t$	0.0028	0.0006***	0.0366**	0.0240**
	(0.66)	(7.66)	(2.04)	(1.97)
ROA $_t$	-0.1095***	-0.0020***	-0.0876	-0.0136
	(-2.78)	(-2.59)	(-0.45)	(-0.18)
LnMV $_t$	-0.5404***	-0.0059***	-0.0442	-0.0219
	(-45.79)	(-25.31)	(-1.41)	(-1.25)
SaleG $_t$	0.0002*	-0.0000	-0.0005	-0.0001
	(1.72)	(-0.72)	(-0.70)	(-0.24)
GuideFreq $_t$			0.0017	0.0006

			(0.46)	(0.43)
Count8k $_t$			-0.0012	-0.0017
			(-0.44)	(-1.00)
Intercept	3.7468***	0.0596***	0.2366	0.1617
	(34.10)	(27.41)	(1.57)	(1.61)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj.-R^2	0.3657	0.3447	0.0246	0.0313
N	8837	8949	6079	5534

Table 2. Summary Statistics

This table presents the descriptive statistics in different samples used in this study. Panel A reports the descriptive statistics of variables in the main tests. Panel B reports the correlation matrix of variables. All variables are defined in the Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Descriptive Statistics

	N	**Mean**	**S.D.**	**p25**	**Median**	**p75**	**Mean: Treated** *(N=4,182)*	**Mean: Control** *(N=5,027)*	**Diff**
$TopicDiff_t$	9,209	50.261	14.183	40.671	49.654	58.517	53.469	47.598	5.868***
$PostDrop_t$	9,209	0.415	0.493	0	0	1	0.813	0	N.A.
$FundSim_t$	9,209	0.266	0.340	0.030	0.294	0.534	0.247	0.282	-0.035***
$Length_t$	9,209	34240	29665	12521	27533	49475	33209	35098	1889.495***
$Issue_{t+1}$	9,209	0.790	0.407	1	1	1	0.788	0.791	-0.003
BM_{t-1}	9,209	0.558	0.624	0.238	0.431	0.719	0.562	0.555	0.007
ROA_{t-1}	9,209	0.026	0.375	-0.014	0.114	0.197	0.058	-0.001	0.059***
$LnAsset_{t-1}$	9,209	5.496	2.053	3.904	5.259	6.899	5.368	5.602	0.234***
$Leverage_{t-1}$	9,209	0.205	0.230	0.016	0.164	0.315	0.202	0.208	-0.006
$SaleG_{t-1}$	9,209	0.277	1.055	-0.046	0.087	0.275	0.236	0.312	-0.076***
$RetVol_t$	9,209	0.039	0.022	0.023	0.034	0.049	0.039	0.039	0.000
$AnnRet_t$	9,209	0.163	0.703	-0.266	0.043	0.387	0.158	0.166	-0.009
HHI_t	9,209	0.140	0.119	0.055	0.105	0.172	0.151	0.131	0.020***
$Beta_t$	9,209	0.919	0.666	0.431	0.856	1.329	0.896	0.939	-0.043***
$AnaCov_t$	9,209	6.862	8.795	0	3	10	6.956	6.783	0.173
$Segment_t$	9,209	1.997	1.439	1	1	3	1.987	2.005	-0.019
$GuideFreq_t$	9,209	0.588	1.567	0	0	0	0.642	0.543	0.099***
$Count8k_t$	9,209	6.718	6.854	1	5	11	6.639	6.784	-0.145
DA_t	9,209	0.380	2.737	-0.083	0.040	0.288	0.177	0.549	-0.372***
$Rated_t$	9,209	0.255	0.436	0	0	1	0.239	0.267	-0.028***

Panel B. Correlation Matrix

	$TopicDiff_t$	$PostDrop_t$	$FundSim_t$	$Length_t$	$Issue_{t+1}$	BM_{t-1}	ROA_{t-1}	$LnAsset_{t-1}$	$Leverage_{t-1}$	$SaleG_{t-1}$
$TopicDiff_t$	1									
$PostDrop_t$	0.182***	1								
$FundSim_t$	-0.013	-0.050***	1							

Length $_t$	-0.424***	0.013	0.066***	1						
Issue $_{t+1}$	-0.102***	-0.012	0.019*	0.029***	1					
BM $_{t-1}$	0.005	-0.001	0.008	-0.038***	-0.029***	1				
ROA $_{t-1}$	0.272***	0.057***	0.054***	-0.046***	-0.152***	0.071***	1			
LnAsset $_{t-1}$	0.201***	-0.035***	0.173***	0.235***	-0.140***	-0.079***	0.370***	1		
Leverage $_{t-1}$	0.083***	-0.031***	0.067***	0.034***	0.033***	-0.171***	0.021**	0.202***	1	
SaleG $_{t-1}$	-0.106***	-0.039***	0.014	0.009	0.057***	-0.108***	-0.144***	-0.100***	-0.015	1
RetVol $_t$	-0.143***	0.006	0.006	-0.043***	0.132***	0.128***	-0.371***	-0.530***	0.016	0.071***
AnnRet $_t$	-0.001	-0.013	0.038***	-0.002	0.049***	0.129***	0.017**	-0.026**	0.015	-0.051***
HHI $_t$	0.159***	0.098*	0.020*	-0.059***	-0.074***	0.071***	0.165***	0.070***	0.033***	-0.069***
Beta $_t$	-0.113***	-0.002***	0.164***	0.258***	0.051***	-0.148***	-0.020**	0.286***	0.026**	0.029***
AnaCov $_t$	0.127***	0.015***	0.177***	0.138***	-0.065***	-0.191***	0.188***	0.695***	0.053***	-0.013
Segment $_t$	0.130***	0.030***	0.043***	0.141***	-0.071***	0.035***	0.185***	0.456***	0.074***	-0.097***
GuideFreq $_t$	0.032***	0.060	-0.001	0.197***	-0.113***	-0.091***	0.132***	0.379***	0.027***	-0.046***
Count8k $_t$	-0.206***	0.048***	0.107***	0.431***	0.005	-0.095***	-0.076***	0.281***	0.077***	0.023**
DA $_t$	-0.120***	-0.057	-0.015	0.066***	0.021**	-0.040***	-0.083***	-0.010	-0.022**	0.029***
Rated $_t$	0.215***	-0.039***	0.165***	0.107***	-0.094***	-0.080***	0.213***	0.706***	0.281***	-0.075***

	RetVol $_t$	*AnnRet* $_t$	*HHI*	*Beta* $_t$	*AnaCov* $_t$	*Segment* $_t$	*GuideFreq* $_t$	*Count8k* $_t$	*DA* $_t$	*Rated* $_t$
RetVol $_t$	1									
AnnRet $_t$	-0.012	1								
HHI $_t$	-0.135***	-0.008	1							
Beta $_t$	0.032***	0.053***	-0.089***	1						
AnaCov $_t$	-0.329***	-0.002	-0.061***	0.255***	1					
Segment $_t$	-0.271***	-0.015	0.155***	0.101***	0.175***	1				
GuideFreq $_t$	-0.248***	0.001	0.092***	0.051***	0.336***	0.242***	1			
Count8k $_t$	-0.116***	0.006	-0.073***	0.370***	0.259***	0.135***	0.217***	1		
DA $_t$	-0.002	-0.018*	-0.083***	0.042***	0.014	-0.039***	0.007	0.099***	1	
Rated $_t$	-0.331***	-0.014	0.100***	0.171***	0.508***	0.362***	0.262***	0.157***	-0.025**	1

Table 3. The Effect of Large Tariff Rate Reductions on Disclosure Topic Difference

This table presents the estimation results for regressions relating disclosure topic difference of firms' MD&A sections in their 10-K files to tariff rate reductions. Standard errors are clustered at the firm level. All variables are defined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: TopicDiff $_t$		
	(1)	(2)	(3)
PostDrop $_t$	**4.6820*** **	**4.2858*** **	**3.9196*** **
	(4.55)	**(4.24)**	**(4.04)**
FundSim $_t$		-0.5019*	-0.5878**
		(-1.70)	(-2.00)
Length $_t$		-0.0001***	-0.0001***
		(-11.01)	(-11.58)
Issue $_{t+1}$			0.1769
			(0.65)
BM $_{t-1}$			-0.3219
			(-1.32)
ROA $_{t-1}$			0.6730*
			(1.89)
LnAsset $_{t-1}$			1.2490***
			(3.69)
Leverage $_{t-1}$			0.9151
			(1.27)
SaleG $_{t-1}$			-0.0836
			(-1.14)
RetVol $_t$			10.9113
			(1.10)
AnnRet $_t$			0.2677**
			(2.21)
HHI $_t$			2.0645
			(0.51)
Beta $_t$			0.0322
			(0.13)
AnaCov $_t$			0.0618
			(1.08)
Segment $_t$			0.0381
			(0.19)
GuideFreq $_t$			-0.0131
			(-0.09)
Count8k $_t$			0.0628*
			(1.88)
DA $_t$			0.0122
			(0.40)
Rated $_t$			0.1483
			(0.17)
Intercept	53.3173***	54.8749***	47.7488***
	(42.65)	(45.70)	(22.40)

Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R^2	0.1875	0.2607	0.2700
N	9,209	9,209	9,209

Table 4. Cross-Sectional Variations in the Effect of Large Tariff Rate Reductions on Disclosure Topic Difference

This table presents cross-sectional variations in the effect of large tariff rate reductions on disclosure topic difference. Panel A reports the results in industries with small versus large import increases after the tariff rate reduction; Panel B reports the results in industries with low versus high pre-reduction import levels; Panel C reports the results in firms with small versus large profit margins; Panel D reports the results in firms with low versus high market shares; Panel E reports results in firms with low versus high fundamental similarity with their peers in the same industry; and Panel F reports the results in firms with short versus long disclosures in the MD&A section of their 10-K files. All variables are defined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. The Magnitude of Import Rise and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Small	*Large*
$PostDrop_t$	**2.7732*** **	**4.7832*** **
	(2.64)	**(3.10)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-2.0100$, P-value (χ^2 test): 0.0000	
Within R^2	0.2876	0.2757
N	7,173	7,005

Panel B. Pre-Reduction Import Level and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Low	*High*
$PostDrop_t$	**0.9089**	**6.2856*** **
	(0.76)	**(5.29)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-5.3767$, P-value (χ^2 test): 0.0000	
Within R^2	0.2571	0.2834
N	6,774	6,955

Panel C. Firm Profit Margin and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Small	*Large*
$PostDrop_t$	**2.5419** **	**4.3607*** **
	(2.19)	**(2.80)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-1.8188$, P-value (χ^2 test): 0.0157	
Within R^2	0.2849	0.2808
N	4,704	4,508

Panel D. Firm Market Share and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Low	*High*
$PostDrop_t$	**1.7788**	**5.6014*****
	(1.23)	**(4.64)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-3.8226$, P-value (χ^2 test): 0.0044	
Within R^2	0.2708	0.2937
N	4,605	4,604

Panel E. Fundamental Similarity and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Low	*High*
$PostDrop_t$	**3.1406*****	**5.5820*****
	(2.77)	**(3.54)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-2.4414$, P-value (χ^2 test): 0.0034	
Within R^2	0.3134	0.2535
N	4,605	4,604

Panel F. Disclosure Length and the Effect of Large Tariff Rate Reductions

	Dependent variable: $TopicDiff_t$	
	(1)	(2)
	Short	*Long*
$PostDrop_t$	**0.4807**	**6.5645*****
	(0.47)	**(4.39)**
	Controls, Firms FEs, Year FEs	
(1)=(2)?	$(1)-(2)=-6.0838$, P-value (χ^2 test): 0.0888	
Within R^2	0.2548	0.2653
N	4,605	4,604

Table 5. Propensity Score Matching

This table explores the impact of large tariff rate reductions on firm disclosure topic difference, using a propensity score matched sample over the (-5, +5) years window centered at the tariff rate reduction events. The treatment groups consist of firms from industries (3-digit SIC code) that experienced a large tariff rate reduction, while the control firms did not experience the reduction. Treated and control firms are matched on the natural logarithm of total assets, book-to-market ratio, and book leverage. I match, without replacement, each treatment firm in the year immediately preceding the event year to 3 control firms with the closest propensity score in same year and Fama-French 12 industry. All variables are defined in the Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: TopicDiff $_t$		
	(1)	(2)	(3)
PostDrop $_t$	**2.6194****	**2.5181****	**2.8201*****
	(2.58)	**(2.36)**	**(2.77)**
FundSim $_t$		-0.2146	-0.3319
		(-0.31)	(-0.49)
Length $_t$		-0.0001***	-0.0001***
		(-3.22)	(-3.21)
Issue $_{t+1}$			1.2059**
			(2.25)
BM $_{t-1}$			0.0224
			(0.04)
ROA $_{t-1}$			-0.0204
			(-0.02)
LnAsset $_{t-1}$			0.1975
			(0.23)
Leverage $_{t-1}$			-0.5805
			(-0.31)
SaleG $_{t-1}$			-0.2111
			(-1.07)
RetVol $_t$			18.2023
			(1.11)
AnnRet $_t$			-0.2360
			(-0.84)
HHI $_t$			11.1955
			(1.53)
Beta $_t$			0.9555**
			(2.09)
AnaCov $_t$			-0.2243*
			(-1.74)
Segment $_t$			0.4632
			(0.94)
GuideFreq $_t$			0.1657
			(0.44)
Count8k $_t$			0.2193**
			(2.05)
DA $_t$			-1.2491**
			(-2.49)

Rated $_t$			0.4673
			(0.38)
Intercept	54.2561***	55.8770***	51.0728***
	(42.96)	(38.85)	(11.47)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R^2	0.0408	0.0808	0.1205
N	1,310	1,310	1,310

Table 6. Parallel Trend

This figure shows the results in testing the parallel trend assumption for the applications of difference-in-differences models. Panel A shows the results from a placebo test where I force the tariff rate reduction events to 3 years before the actual event year; Panel B shows the results from the regression of disclosure topic difference on indicators of the number of years before and after the event years. All variables are defined in the Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Placebo Test

	Dependent variable: $TopicDiff_t$
	(1)
$PostDrop_t$	2.2908
	(1.18)
	Controls, Firms FEs, Year FEs
Adj-R^2	0.2649
N	9,209

Panel B. The Dynamic of the Impact

	Dependent variable: $TopicDiff_t$
	(1)
PreDrop_2	2.7262
	(1.09)
PreDrop_1	1.6509
	(1.09)
Drop_0	3.1718**
	(2.53)
PostDrop_1	3.7676***
	(2.92)
PostDrop_2	2.9308**
	(2.28)
PostDrop_3	1.7595
	(1.41)
PostDrop_4	2.3303*
	(1.74)
PostDrop_5	0.5058
	(0.31)
	Controls, Firms FEs, Year FEs
Adj-R^2	0.2756
N	1,720

Table 7. Disclosure Differentiation in Response to Tariff Rate Reductions and Firm Future Performance

This table presents the results for regressions relating firm future performance to firm disclosure differentiation in response to large tariff rate reductions. Column (1) measures the firm's future performance using the firm's percentile of sales in the 3-digit SIC industry; column (2) measures the firm's future performance using the firm's percentile of return on assets in the 3-digit SIC industry; column (3) measures the firm's future performance using the firm's percentile of Tobin's Q in the 3-digit SIC industry. All variables are defined in the Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Dependent variable:	$Rank\_Sale_{t+1}$	$Rank\_ROA_{t+1}$	$Rank\_Q_{t+1}$
	(1)	(2)	(3)
$TopicDiff_t$	-0.0219	-0.0485	0.1022**
	(-0.67)	(-1.17)	(1.99)
$PostDrop_t$	-7.4713***	-4.5984	7.5864*
	(-2.63)	(-1.18)	(1.73)
$TopicDiff_t \times PostDrop_t$	**0.1095****	**0.1047***	**-0.0730**
	(2.50)	**(1.65)**	**(-1.00)**
BM_{t-1}	-2.6373***	-5.7026***	
	(-6.51)	(-9.03)	
ROA_{t-1}	2.0230***		-0.3191
	(2.97)		(-0.23)
$LnAsset_{t-1}$	6.8903***	-0.4481	-5.9628***
	(14.05)	(-0.57)	(-6.50)
$Leverage_{t-1}$	0.2252	0.4447	4.0857*
	(0.14)	(0.26)	(1.83)
$SaleG_{t-1}$	0.5652***	0.2867	0.5275**
	(3.41)	(1.33)	(2.01)
RD_{t-1}	0.1332	-9.5420***	1.4726
	(0.06)	(-3.53)	(0.41)
$RetVol_t$	-61.561***	-42.633**	-19.1769
	(-4.24)	(-1.97)	(-0.76)
$AnnRet_t$	2.3501***	4.8753***	4.4290***
	(12.62)	(13.19)	(12.02)
$GuideFreq_t$	0.02567	0.3105	-0.0506
	(0.18)	(1.21)	(-0.19)
$Count8k_t$	0.1450***	-0.0457	-0.2537**
	(2.96)	(-0.63)	(-2.44)
DA_t	0.0221	0.0202	-0.0606
	(0.52)	(0.27)	(-0.69)
$Rated_t$	-0.9468	-4.1422**	-0.0103
	(-0.75)	(-2.39)	(-0.01)
Intercept	30.0177***	58.1670***	72.1945***
	(10.22)	(12.13)	(11.67)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R^2	0.1622	0.0706	0.0755
N	9,190	9,182	9,191

Table 8. Market Response to Disclosure Differentiation

This table presents the results for regressions relating cumulative abnormal returns around the firm's 10-K filing date to firm disclosure differentiation in response to large tariff rate reductions. All variables are defined in the Appendix A. All continuous independent variables are winsorized at their 1st and 99th percentiles. t-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: CAR(-1, 5) $_t$		
	(1)	(2)	(3)
PostDrop $_t$	0.0074	0.0068	0.0159
	(0.67)	(0.62)	(0.76)
TopicDiff $_t$	0.0001	0.0001	0.0000
	(0.83)	(0.91)	(0.17)
TopicDiff $_t$×*PostDrop* $_t$	-0.0002	-0.0002	-0.0003
	(-0.88)	(-0.85)	(-0.90)
FundSim $_t$		-0.0004	-0.0054
		(-0.09)	(-0.90)
Length $_t$		0.0000	0.0000
		(0.61)	(1.18)
Intercept	-0.0092	-0.0112	0.0051
	(-1.41)	(-1.40)	(0.29)
Firm FE	No	No	Yes
Year FE	No	No	Yes
Adj R^2	0.0002	0.0002	0.0069
N	8,314	8,314	8,314

Figure 1. The Trend of Disclosure Topic Difference over Time

This figure presents the distribution of disclosure topic difference over time. The x-axis is firm fiscal year, and the y-axis is disclosure topic difference of the MD&A sections in firms' 10-K files. The red dashed line marks the mean disclosure topic difference through all firm-years; the black line connects the disclosure topic difference value points in each year; the blue belt shows the 95percent confidence interval of the disclosure topic difference values in each year.

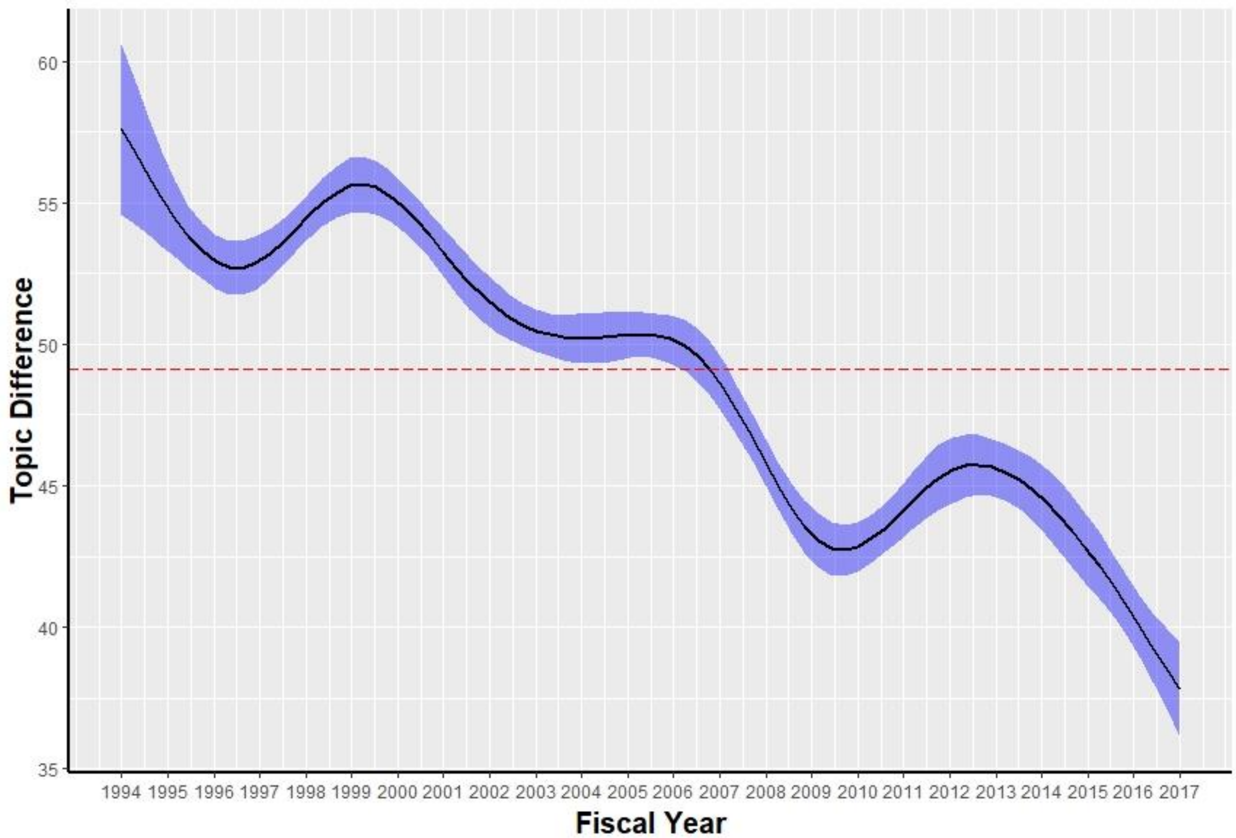

Figure 2. Fundamental Changes and Disclosure Differentiation

This figure presents the results from the path analysis for the impact of large tariff rate reductions on disclosure topic difference through the channel of changes in firm fundamental similarity to its 3-digit SIC industry peers. All variables are defined in the Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. *z*-statistics are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.