Firm-Level Exposure to Trade War: Measurement and Effects

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Abstract

We develop a text-based measure on Chinese listed firms' international trade exposure (textual trade exposure or TTE) using 12,325 earnings conference transcripts between 2006 and 2019. We then use the TTE measure to study the impact of the 2018-2019 U.S.-China trade war on firms. Not only does our measure effectively capture the financial impact of the trade war, proven by the fact that around the dates when higher tariffs were announced, firms with one standard deviation higher of TTE experienced 0.20% larger declines in market values, it also has a unique advantage to measure the impact on the domestic market firms who do not directly participate in international trade but affected through the supply chain. We then find a surprised, positive effect on the short-term profits and sales for the high TTE firms after the trade war. Further heterogeneity analysis confirms the positive effect comes solely from the domestic market firms. After the trade war, export-oriented firms turn to domestic suppliers for purchasing material and services, leading to a scale expansion for the latter.

JEL Codes: D80, F10, F51, G12, G14

Keywords: Trade War; Textual Analysis; Trade Exposure; Event Study; Heterogeneity; Domestic Firms

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1. Introduction

A widespread consensus among economists is the importance of international trade to a country's economic development is way beyond the trade sector. Through the development of complex global-cum-domestic supply chains, shocks from international trade often propagate and amplify through the domestic production networks and raise the macroeconomic risk to the whole economy (Caliendo and Parro, 2014). Therefore, when the Trump administration started a "trade war" with China in March 2018 by issuing a serial of presidential memorandum to raise the tariff on Chinese import, and China actively retaliated with extra tariff for the US goods, worries about "trade war" would impact beyond the trade sectors and lead to catastrophic impact to the world's two largest economies immediately arose. For this reason, timely research on the overall impact of the trade war on the firms both directly and directly impacted is greatly in need for guiding future policies.

Several studies made efforts on this front (Benguria et al., 2020; Huang et al., 2020; Jiao et al., 2020), but nevertheless, focus on firms from the trade sector while ignoring firms that indirectly impacted. To mitigate this gap, what we need is a good measure that can both accurately quantify the impact of the trade war and measure the impact beyond the trade sectors.

In this paper, we use textual analysis of annual earnings conference transcripts from Chinese listed firms between 2006 and 2019 to construct a firm-level measure of the extent firms exposed to trade and thus risk from trade war over time. Hassan et al. (2019) are the first to use the earnings conference transcripts of the US listed firms to measure the political risk. Similarly, Caldara et al. (2020) applied textual analysis to the same corpus to measure firms' uncertainty specific to trade policy. Our study is the same in spirit but the first to use the transcript from Chinese list firms' earning conference and apply it to study the impact of the trade war. China Securities Regulatory Commission Encouraged listed firms to hold annual earnings conference since 2006 and until now, a majority of Chinese listed firms (56%), hold regular earnings conferences with their investors, analysts, and other interested parties, in which management responds to concerns about the firm's strategy, challenge, and future plan from participants. We quantify the risk faced by a given firm to trade shocks at a given point in time based on the share of conversations on conference calls that centers on risks associated with trade. Given the interactive, instant, and opening features of the earnings conference, its conversation is subjected less to the management's window-dressing and agenda-setting, which is commonly found in other formal public documents of the firms (e.g., periodical reports, announcement, and news reports).

Our empirical findings also validate this unique advantage of such corpus. We labeled this new measure textual trade exposure (hereafter TTE). We validate that firms' TTE varied intuitively over time and across industries, that it correlates with conventional trade indices such as exports, imports, tariff exposure, and trade policy uncertainty. Most importantly, using an event study based on the initial announcement of the extra tariff on March 22, 2018, we confirm listed firms with high TTE have significantly decrease of market value than their low TTE counterparts upon the announcement, specifically, one standard deviation higher of TTE in 2017 for firms is associated with a 0.50% decrease on cumulative abnormal return in the first month after trade war. More importantly, from the summary statistics, we confirm the TTE measure is good at capturing the risks from trade war on the domestic market firms. Among the high TTE firms in 2017, for example, about 57% of firms directly participated in trade while 43% of them indirectly participated through the supply chain.

Upon validating our new measure, we then use our measure to explore the effect of the trade war on firms. Using firms' quarterly panel, we find that after 2018 March, firms with higher TTE exhibit a marginal increase in profits, sales, and cost. Further heterogeneity tests confirm the effect is driven only by the domestic market firms with high trade exposure via the supply chain. We confirm that after the trade war broke out, to avoid the increasing cost from the punitive tariff, the export-oriented firms with high TTE increasingly swift their top 5 suppliers to domestic firms. A scale expansion of the domestic market firms with high TTE thus is confirmed: both the sizes of cost and sale increase for them after the trade war, correspondingly, the operating cost, sale and distribution (S&D) expanse, and general and administrative (G&A) also increase. For export-oriented firms, the pertinent statistics decrease by TTE after the trade war, but statistically insignificant.

This paper joins a nascent literature accessing the impact of the US-China trade war on Chinese firms and firms' short-term responses. Earlier efforts have been focused on the impact on US firms. For example, Fajgelbaum et al. (2019) and Amiti et al. (2019) discover a loss of 0.04% of the US GDP as a result of both the US extra tariffs on trade partners and retaliatory tariffs these countries imposed on the US. On the other hand, Amiti et al. (2020) demonstrate a decline in investment for U.S. listed firms as a result of the trade war. Huang et al. (2018) further confirm a decline of market value to the US listed firms exporting to China around the March 2018 announcement. On the other hand, Using Chinese listed firm's annual reports, Benguria et al. (2020) construct a trade policy uncertainty (TPU) index that followed the method proposed by Caldara et al. (2020) and confirms a reduced of investment, R&D expenditure, and profit of the Chinese firms with high TPU. Using detailed sale and price data, Jiao et al. (2020) discover no adjustment on sales of firms facing a higher tariff. Unlike them, our paper discovers a bigger and positive effect of the trade war on domestic market firms through the supply chain.

The most novel aspect of our paper is the firm-level measure of risk to trade based on a textual analysis of firms' earnings conference call transcripts. We follow the methods proposed by the recent works on the firm's exposure to the risk of Brexit (Hassan et al., 2020), political risk in general (Hassan et al., 2019), and trade policy uncertainty (Caldara et al., 2019), but propose a specific procedure to dealing with Chinese text of earnings conference transcripts. For example, to construct a Chinese dictionary of trade-related terms, we combine several new sources of domain-specific dictionary and the new word embedding (*word2vec*) method.

2. Data, Measure, and Validation

We collect transcripts of all 12325 online earning conferences of 2106 firms listed in China between 2006 and 2019 from Chinese Research Data Services (CNRDS). During our sample window, firms host at most one earning conference every fiscal year. On Earning conferences, financial analysts and other market participants listen to senior managers presenting their views on the company's state of affairs and ask these company officials questions about the firm's financial performance and discuss future developments (Hollander et al. 2010). Online earning conferences typically begin with a presentation by a senior manager, during which executives (e.g., the chief executive officer or the chief financial officer) share information they wish to disclose or emphasize, followed by a question-and-answer (Q&A) session interacted with market participants (usually, but not limited to, financial analysts). Our measure of trade exposure is constructed using the Q&A section of earning conferences.

Online earning conferences of Chinese listed firms have several characteristics which make them appropriate for measuring firms' exposure to the trade war. First, unlike a firm's website or periodical reports, earning conference is interactive in the sense that market participants can raise questions at any time during the conference and managers ought to answer them immediately. Prior research shows that earning conferences provide information beyond announcements, e.g. annual reports; and that much of these conferences' informative-ness is attributable to their interactive nature, which allows for more extemporaneous disclosures towards specific concerns raised by conference participants (Frankel et al. 1999; Matsumoto et al. 2011; Lee 2016; Li et al. 2020). Since Q&A section is more extemporaneous and therefore offers far fewer opportunities for managers to pick discussion topics (Lee 2016), using Q&A section only to measure trade exposure mitigates the concern that managers might only report what is good and conceal what is bad and cover up the real impact of the trade war.

Second, the online earning conference is completely open to market participants. In other words, there are no eligibility requirements to participant in earning conference. Any stakeholders, such as investors (even potential investors), financial analysts, suppliers, clients, or competitors can anonymously join the online earning conference and raise questions. Many other information disclosure channels, including the shareholder meeting and the on-site investigation of financial analysts are less open than the online earning conference: only shareholders can attend the shareholder meeting and the on-site investigation of financial analysts is inaccessible to non-institute investors. The vast participants base and the impromptu interactive nature of the online earning conference guarantee the unbiasedness of information disclosed, making it a proper data source to measure exposures of Chinese listed firms to the trade war[1]. More detailed institutional background of online earning conference in China can be found in Online Appendix A1.

To see the advantage of online earning conference more directly, let's go back to the case in table 1. In panel C, we show the whole section of management discussion and analysis in the 2018 annual report of Hunan Kaimeite Gases. In the annual report, the firm management only mentioned US-China trade war once. It merely stated that the trade war and trend of anti-globalization will impact China's total exports, but did not explain whether the trade war will affect the firm itself, let alone the firm's response to the trade war. However, in the online earning conference shown in panel B, the firm management mentioned that the trade war may be beneficial for Hunan Kaimeite Gases, since downstream firms might switch to domestic suppliers after the trade war. In this case study, online earning conference provides more detailed information than annual report, which further validates using earning conference transcripts as data source.

[1] In fact, we show in appendix B5 that, unlike online earning conference, firm's annual report is not a good source to measure trade war exposure.

We obtain additional data from the following sources: firm's daily stock information and quarterly basic balance sheet (e.g. total assets) and income statement (e.g. quarterly earnings) from China Stock Market & Accounting Research Database (CSMAR), firm's annual exports and imports during 2011-2016 from General Administration of Customs, and HS8 level U.S.-China trade war tariffs from Fajgelbaum et al. (2020). Finally, we acquire transcripts of Chinese listed firms' annual reports from Wind Database. In particular, information about listed firm's top 5 clients and suppliers is scraped from the transcripts of annual reports. Table A2 in Online Appendix A3 provides summary statistics of all variables.

Now, we introduce our firm-level measure of textual trade exposure (henceforth referred as TTE). We begin by defining TTE as the share of the Q&A section between conference participants and firm managers that centers on trade issues. In a second step, we argue that this measure can be interpreted as firm's exposure to trade issues, especially, the trade war.

2.1 Defining the Measure of Textual Trade Exposure (TTE)

We begin with a simple objective: measure the share of the Q&A section between market participants and firm managers that centers on trade issues. Clearly, any trade issue raised during an earning conference will tend to be of some concern either for the firm's managers or its investors. Thus, quantifying the share of discussion about trade related topics reveals firm's trade exposure.

The starting point for us to measure firm-year level TTE is the construction of trade term dictionary. From Sogou Pinyin[2], we construct trade term dictionary by combining three dictionaries related with international trade and investment[3]. Additional trade terms are manually supplemented from Dictionary of Trade Policy Terms (Goode, 2013), which lists terms routinely mentioned in international trade negotiations. The ultimate trade term dictionary includes 500 terms. Table B1 in Online Appendix B1 shows trade terms and their frequencies in transcripts of earning conferences.

[2] Initially released in 2006, Sogou Pinyin is the most popular input method in China. It uses search engine techniques to analyze and categorize the most popular words and phrases on the Internet. Sogou Pinyin also established a dictionary database (https://pinyin.sogou.com/dict/) containing a vast scope of topics.

[3] Namely, the three dictionaries are international trade terms, international investment terms, and foreign trade lexicon.

Given this trade term dictionary **T**, our textual trade exposure (TTE) is measured as follows. First, we divide each earning conference transcript of firm *i* in year *t* into a list of phrases, $b = 1, \ldots, B_{it}$. Word-segmentation algorithm *jiebaR* is used to cut up Chinese sentences, and numbers and punctuations are removed from the phrase list. Second, we count the total number of phrases belonging the trade term dictionary **T**, and divide by the total number of phrases in the transcript. That is, we calculate the frequency of trade terms:

$$TTE_{it} = \frac{\sum_b^{B_{it}} 1[b \in \boldsymbol{T}] * w_b}{B_{it}}, \tag{1}$$

where $1[\cdot]$ is the indicator function. The first term in the numerator thus simply count the number of phrases belonging to the trade term dictionary. In our baseline specification, the weight of each trade term w_b is set to 1, assuming that each phrase in the trade term dictionary is equally associated with the discussion of trade issues. Additionally, as a robustness check, we calculate the semantic similarity of each trade term to the key word "trade war" (贸易战) as the weight w_b, using the word-embedding algorithm *word2vec*. In short, our measure of firm-year level TTE is the (weighted) frequency of phrases related to trade issues. Table B4 in Online Appendix B4 reports excerpts of the 10 transcripts with the highest TTE, which illustrates that our TTE measure correctly identify discussions related to trade issues.

Before moving on to the validation of our TTE index, we here further discuss several considerations in the construction of TTE. First, one may suspect that the composition of trade term dictionary is ad-hoc, which leaves TTE vulnerable to misspecification of the dictionary. Admittedly, the inaccuracy of training dictionary is a general concern in text analysis; however, in our situation, misspecification of the dictionary has only minor impact on the measure of TTE. After manual readings of hundreds of transcripts, we find the number of unique trade-related phrases is quite limited and almost all trade phrases we encounter are in the trade term dictionary. In fact, more than two thirds of trade terms in the dictionary never appear in any transcript of earning conference. On the other hand, we construct alternative trade term dictionaries by excluding one of the four components of baseline dictionary (three dictionaries from Sogou Pinyin, and terms from Dictionary of Trade Policy Terms) and re-measure TTE. All these alternative TTE measures are highly correlated with the baseline one, as shown in Table B2.

Second, the weighting scheme used in baseline specification is different from traditional weighting method tf-idf (term frequency inverse document frequency) (Sparck Jones 1972; Salton and McGill 1983; Salton and Buckley 1988)—in our setting, term frequency is not deflated by its document frequency. The assumption behind tf-idf weighting method is that terms appear in the majority of documents have less relative importance, which is inappropriate for trade-related terms in our situation. Since trade term dictionary is predetermined, it is natural to put equal weight on each trade term, as in our baseline specification. In Online Appendix B2, we consider using the semantic similarity between trade terms and the key word "trade war" as term's weight w_b. The intuition is that trade terms with more similar meanings with "trade war" should have higher weight in the measure of TTE. In order to calculate such semantic similarity, we take advantage of a word-embedding algorithm, *word2vec*. The alternative TTE constructed in this robustness check is also highly correlated with the baseline one as shown in Figure B1.

2.2 Validation

In this section, we explore the properties of TTE, to corroborate that it captures firm-level exposure to the trade war. First, we show descriptive statistics of TTE over time and across industries, which accord with the pattern of US-China trade war. We then illustrate that to capture firm-level trade war exposure, TTE has advantage over traditional measure such as tariff exposure and trade policy uncertainty (TPU). To further validate our TTE measure, we apply the event study approach to the March 22, 2018 announcement by Trump to start the trade war, and document that firms with higher TTE experience larger stock market losses.

To begin with, Figure 1 Panel A plots the across-firm distribution of non-zero TTE in each year during 2011-2019. Before the break of the trade war in 2018, the average levels of TTE are low across Chinese listed firms, and the distributions of TTE are quite stable over time. After the break of US-China trade war, we find a large spike of TTE in 2018 and the measure stays at high position in 2019. The mean and the 95-percentile of TTE almost double from 2017 to 2018, indicating a steep rise of trade-related topic discussion in online earning conferences. Another message from Panel A is that the variation of TTE across Chinese listed firms is large: while the average TTE raises twice after the trade war, some firms are not affected by the trade war and their TTEs remain close to zero. US-China trade war has heterogeneous impact towards Chinese listed firms.

In Panel B of Figure 1, we plot the average TTE across industry before and after the trade war. Industries are ranked by their average TTE before the trade war. Three patterns manifest themselves in this graph. First, export-intensive industries such as electronics, textiles, and machinery exhibit larger TTEs before the trade war[4]. Second, almost all industries experience increases of TTE after the trade war and those with higher TTEs before the break of trade war tend to have higher TTEs after: the Pearson correlation between TTE before and after the trade war is 0.475. Third, those industries with largest increase of TTE after the trade war, e.g. manufacture of general purpose machinery, manufacture of metal products and manufacture of automobiles, consist of more tariff-targeted products[5]. Complementarily, we show in Appendix B6 that our TTE measure is positively correlated with tariff exposures[6].

[Figure 1 here]

As shown in Figure 1, TTE's variations across time and industry are consistent with the pattern of the trade war, which indicates TTE as a proper measure for firm-level exposure to the trade war. Now, we illustrate that TTE has advantage over traditional exposure measure in the literature such as tariff exposure and trade policy uncertainty(TPU). First, tariff exposure only applies to firms that directly export and/or import tariff-targeted products. For domestic market firms, tariff exposures are zero mechanically. On the contrary, a majority of domestic market firms have non-zero TTEs. Thus, to explore trade war's effects on domestic market firms, which is the focus of our paper, it is better to use TTE than tariff exposure.

Another widely-used exposure measure is TPU, as in Caldara et al. (2020) and Benguria et al. (2022). Similar with TTE, TPU is also a text-based measure and its construction can be found in Appendix A3. Basically, TPU counts the frequency of joint instances of trade terms and uncertainty terms (such as uncertainty, unclear, unexpected, etc.), and captures firm-level risks toward trade-related issues. Since we use the same trade term dictionary to construct TTE and TPU, they are moderately correlated with a Pearson coefficient 0.315, as shown in Figure 2 Panel A.

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[4] Based on BACI database from CEPII, electronics, machinery, and textiles account for 27.4%, 22.2%, and 15.2%, respectively, of total export of China in 2017.

[5] In the U.S.-China trade war, U.S. government targeted import tariffs to products which Chinese government wants to support, especially those mentioned in the "Made of China 2025" plan. These products cover a wide range of sectors such as raw material, construction machinery, aerospace, agricultural equipment, electronics, medical devices, etc.

[6] The construction of export and import tariff exposure can be found in Appendix A3.

Now we illustrate that TTE is a better measure than TPU to explore trade war's effect on firms. The reasons are threefold. First, TTE measures the intensity of trade-related-topic discussion, while TPU measures the risk related to trade issues. By construction, TPU only considers potential risks brought by the trade war, but not possible benefits. That is to say, TPU captures the negative impact of the trade war, while omits its positive prospect. On the contrary, TTE just documents the share of trade-related discussion, not presuming that the trade war will do harm to firms. In fact, as shown in section 3, we document a positive effect of the trade war on domestic market firms, which cannot be reproduced using TPU.

Second, TTE is more responsive to the trade war than TPU. In Figure 2 Panel B, we depict annual averages of standardized TTE and TPU[7]. Similar with Figure 1, there are spikes of standardized TTE and TPU in 2018. Nevertheless, the spike of TTE is three times higher than that of TPU, which implies TTE responses to the trade war more sensitively than TPU. In addition to the intensive margin, TTE is also more responsive on the extensive margin. As shown in Panel C, after the trade war, the share of firms with non-zero TTE increases from 0.7 to 0.8, while the fraction of non-zero TPU remains around 0.15. Another message from Panel C is that, the ratio of zero in TPU is far larger than that in TTE. Since TPU counts the co-occurrence of trade terms and uncertainty terms in narrow neighborhoods, it naturally contains masses of zeros, which might lead to non-negligible measurement error. In other words, having zero TPU does not mean the firm is not affected by the trade war. On the contrary, TTE has much fewer zero values: measurement error attributed to this zero-value issue is slighter for TTE. In Panel D and E, we duplicate Panel B among export-oriented firms and domestic market firms, respectively[8]. Similarly, TTE has more significant respond after the trade war in both firm groups.

Third, applying a horse racing specification, we show the effect of TTE on firm outcomes dominates that of TPU. In brief, we run regressions of firm outcomes (log sales and costs) on standardized TTE and TPU, controlling for firm total asset, age, and two way fixed effects, i.e. firm fixed effects and time (year-quarter) fixed effects. As shown in Table B5, in all six columns (two firm outcomes × three firm groups), the beta coefficients of TTE dominate those of TPU, both economically and statistically.

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[7] To standardize TTE and TPU, we first subtract their sample means, then divide by their standard deviations. After standardization, TTE and TPU have the same magnitude and can be compared directly.

[8] In this paper, we define export-oriented firms as those that export or import at least once during 2011-2016. Firms never export and import during 2011-2016 are classified as domestic market firms.

[Figure 2 here]

Until now, we've shown that the descriptive statistics of TTE concord with the pattern of the trade war, and that TTE have advantage over tariff exposure and TPU. To further validate TTE as an appropriate measure of firm-level exposure to the trade war, we explore TTE's effect on firm's stock market performance. We apply the event study approach to Trump's announcement of the trade war against China on 2018/3/22. Specifically, we first calculate firm's cumulative abnormal returns (CAR) during several time windows. Then we regress CARs on firm's average TTE before the trade war. As demonstrated below, firms with higher TTE experience larger stock market losses after the trade war.

To access the trade war's impact on firm's stock market performance, we define cumulative abnormal returns (CAR) as the main dependent variable of interest. Let us denote the event date, Mar. 22, 2018, as date 0. The variable *X* and *Y* represent the beginning and ending days of a time window. Specifically, we compute the cumulative abnormal return of firm *i* in time window [*X*, *Y*] as:

$$CAR_i^{[X,Y]} = \sum_{t=X}^{Y} AR_{it}\,, \tag{2}$$

where AR_{it} is the abnormal return for firm *i*'s equities on date *t*, calculated using the market model. Following the standard practices in finance literature (e.g., Schwert, 1981; MacKinlay, 1997), we estimate the firm-specific market model parameters beta and alpha in the period from 2017/9/1 to 2018/2/28, and calculated the abnormal returns for each firm. Specifically, we first run regression of firm *i*'s return on the market return during 2017/9/1 to 2018/2/28. The regression coefficient of the market return is firm *i*'s beta value β_i, and the intercept is firm *i*'s alpha value α_i. Then we calculate $AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}$, where R_{it} and R_{mt} are the return on date *t* for firm *i* and the market respectively[9].

We use firm-level average TTE before the trade war as our main independent variable. The reason to use firm's TTE before the trade war is to mitigate endogeneity issue, since this variable is pre-determined when the trade war began. Using TTE before the trade war as the explain variable avoids confounding factors which affect discussion of trade-related issues in online earning conference and firm's stock price at the same time. Now we explore the relationship between average TTE before the

[9] The market return is the value-weighted returns for all firms in the China Stock Market & Accounting Research Database (CSMAR) database.

trade war and cumulative abnormal returns in different time windows. Specifically, we run the following regression:

$$CAR_i^{[0,t]} = \delta_k + \beta^{[0,t]} TTE_i + X_i \Gamma + \varepsilon_i, \qquad t = -3, \dots, 9 \tag{3}$$

where $CAR_i^{[0,t]}$ is firm *i*'s cumulative abnormal return in time window [|*t*| weeks before 2018/3/22, 2018/3/22] if $t < 0$, [2018/3/22, *t* weeks after 2018/3/22] if $t > 0$, and the abnormal return on 2018/3/22 if $t = 0$. δ_k is industry-level fixed effect and X_i are firm-level controls including log total assets and age. $\beta^{[0,t]}$ is TTE's effects on firm's cumulative abnormal return in the corresponding time window. Standard errors are clustered at industry level. Figure 3 summarizes the results. Firms with higher average TTE before the trade war experience a relatively lower CAR during the first month after the trade war. For example, a one standard deviation higher TTE is associated with a 0.043 standard deviation decrease of abnormal return on 2018/3/22 and with a 0.021 standard deviation decrease of cumulative abnormal return during the first month after the trade war[10]. Complementary to previous researches focusing on the immediate response of firm's stock price to trade war, e.g. Huang et al. 2018, our findings illustrate the short and mid-term negative effects of the trade war on listed firms' stock returns. Besides, TTE has no significant effect on stock returns before the trade war. In Appendix B8, we repeat the same regressions in (3) with alternative TTE measures, which obtains similar results. To sum up, firms with higher TTE experience greater stock market loss after the announcement of the trade war, which further confirms that our TTE measure captures firm-level exposure to the trade war.

[Figure 3 here]

3. Using TTE to Identify the Trade War's Effect

Previous section has validated our TTE measure as firm-level exposure to the trade war. Then it is natural to evaluate the trade war's treatment effect on Chinese listed firms utilizing the TTE measure. Specifically, we estimate the trade war's effect on firm outcomes such as sales and costs using the following specification:

$$y_{it} = \tilde{\theta} \overline{TTE_i} \times post_t + X_{it}' \Gamma + \alpha_i + \lambda_t + \varepsilon_{it}, \tag{4}$$

where y_{it} is the firm-level outcome of interest (log sales and costs); $\overline{TTE_i}$ is the firm-level average TTE before the trade war; $post_t$ is a dummy variable equals to 1 after the trade war (since 2018 quarter 1); X_{it} are firm controls including log firm asset and firm age; α_i and λ_t are firm fixed

[10] The standard deviation of average TTE before trade war is 0.00183, and the standard deviations of CAR on 2018/3/22 and during the first 4 weeks after the trade war are 0.038 and 0.175, respectively. Thus, the two scale-free coefficients of TTE on cumulative abnormal return can be calculated as 0.00183× (-0.888)/0.038=-0.043, and 0.00183× (-1.986)/0.175=-0.021.

effects and time (year-quarter) fixed effects, respectively. Inferences are based on standard errors clustered at the firm level. The sample period is from 2011 to 2019. Summary statistics of all firm-level variables are presented in Table A2 panel B.

The specification in equation (4) needs further explanation. In this continuous-treatment DID setting, we utilize $\overline{TTE_i}$, average TTE before the trade war, as the treatment variable. Although TTE is an appropriate measure for firm-level exposure to the trade war, we should admit that measurement error still exists, which is somewhat inevitable in text analysis. Precisely, TTE can be decomposed into two parts: one is firm's treatment dose to the trade war, and the other is measurement error. Since TTE is haunted by measurement error, the best one can hope is to identify the sign of the trade war's treatment effect[11]. To identify the direction of the trade war's effect, we need that TTE's measurement error is uncorrelated with the error term ε_{it}, i.e. the standard measurement error assumption holds, conditional on firm controls and two-way fixed effects. To achieve that uncorrelated-ness, TTE before the trade war is applied as the treatment variable. Before the trade war, since $post_t$ equals to 0, $\overline{TTE_i} \times post_t$ is also 0 and uncorrelated with ε_{it}. After the trade war, since $\overline{TTE_i}$ is pre-determined, it is innocuous to assume $\overline{TTE_i}$ is uncorrelated with ε_{it}. Thus, as proven in Appendix C1, $\tilde{\theta}$ in equation (4) identifies the sign of the trade war's treatment effect. Bearing that in mind, we should focus more on signs of regression coefficients than their numbers when interpreting regression results.

[Table 2 here]

Table 2 presents estimation results of the trade war's effect on Chinese listed firms' sales and costs. For the sake of interpretation, we standardize average TTE before the trade war across all listed firms. Column (1) and (2) indicate that across all Chinese listed firms, TTE has no significant effect on total sales and costs after the trade war. Although the coefficients are not statistically significant, their signs are positive. In fact, as shown in Appendix C2, firms with higher TTE even experience slightly higher profits than those with lower TTE after the trade war. That is to say, as a whole, US-China trade war does not exert negative effect on Chinese listed firms.

However, these results are somewhat different from the previous literature on firm's response after the trade war. Existing literature mainly focused on trade war's impact on exporters and/or importers, both in the U.S. and in China, e.g. Fajgelbaum et al. (2020), Amiti, Redding and Weinstein (2019), Cavello

[11] Standard measurement error induces attenuation bias, which while makes coefficients inconsistent, keeps their signs unchanged.

et al. (2019), Handley, Kamal and Monarch (2020) for U.S. firms and Jiao et al. (2020), Benguria et al. (2022) for Chinese firms. These researches document significant decline in sales and/or profit margins for exporters and/or importers[12]. The reasons causing different estimated effects of the trade war between ours and previous studies are twofold. First, our data sample consists of listed firms while past literature focus on exporters/importers. Second, previous researches mostly utilize tariff exposure and/or TPU to measure the trade war's impact on firms while we take advantages of TTE. As discussed in section 2.2, TTE has advantage over traditional measures such as tariff exposure and TPU. As constructed, TTE reflects the discussion intensity of trade-related issues in a firm's online earning conference, which contains more comprehensive information about a firm's response to the trade war.

The results in column (1) - (2) demonstrate weakly positive effects of the trade war on Chinese listed firm's outcomes. This somewhat counter-intuitive estimates, as shown in column (3) - (6), is driven by domestic market firms. Clearly, the trade war has wide-spread effects among firms, not only directly affects exporters and importers, but may also have indirect impacts towards domestic market firms through supply chain connection, as implied in Huang et al. (2018). Considering that, the trade war's effects could be heterogeneous between export-oriented firms and domestic market firms. Thus, we partition all Chinese listed firms into these two subgroups and re-conduct regression in equation (4)[13]. Column (3) - (4) demonstrates that among export-oriented firms, those with higher TTE manifest no significant changes in sales and costs than those with lower TTE, after the trade war. This result implies that export-oriented firms are barely affected by the trade war. Actually, the fact that these firms' sales are quite stationary after the trade war is consistent with Jiao et al. (2020), which documents that Chinese exporters diverted their exports from the U.S. to other foreign countries after the trade war. On the contrary, as shown in column (5) - (6), domestic market firms with higher TTE experience significant increases in total sales and costs than their lower TTE counterparts after the trade war. A one standard deviation rise of TTE will lead to 8.3% and 5.7% growth of sales and costs, respectively. These significantly positive numbers indicate that the trade war has positive effects to Chinese domestic market firms: their scales expand (higher sales and costs) after the trade war.

[12] Fajgelbaum et al. (2020) find that, following U.S. tariff increases, imports declined significantly and the tariff burden fell completely on U.S. domestic consumers. Amiti, Redding and Weinstein (2019), Cavello et al. (2019) show that U.S. tariffs were almost entirely borne by U.S. importers. Handley, Kamal and Monarch (2020) find that U.S. exporters who rely on Chinese inputs suffered a loss in their exports through a supply chain channel. Jiao et al. (2020) find that Chinese exporters reduce significantly their exports to the U.S. while their domestic sales and exports to other foreign markets barely adjusted. Benguria et al. (2022) find the rise of TPU brought by the break of trade war is associated with lower firm profits.

[13] We combine exporters and importers into a single group, i.e. export-oriented firms, since 80% of these firms have both export and import experiences.

To further understand the trade war's effects on firm's other outcomes, we decompose total costs into several components and redo estimation in equation (4). The results are displayed in Appendix C3. Domestic market firms with higher TTE increase their production costs and sales & distribution expenses, while export-oriented firms with higher TTE do not. These results further confirm that domestic market firms expand their sizes after the trade war.

3.1 Robustness

The findings that the trade war has positive effect on domestic market firms is somewhat unexpected. Thus, it is necessary to confirm that our findings above are robust. To begin with, we add firm's TPU as another firm control and re-estimate equation (4). If TPU captures additional information about firm's exposure to the trade war that TTE fails to catch, i.e. TPU contains part of the error term ε_{it}, then we will expect: (1) the coefficient of TPU is significant; (2) the coefficient of $\overline{TTE_\iota} \times post_t$ has significant change. However, as shown in Table 3 panel A, coefficients of TPU is insignificant, both economically and statistically, for both export-oriented firms and domestic market firms. Further, coefficients of $\overline{TTE_\iota} \times post_t$ barely change compared with those in Table 2. This robustness check, complementary to arguments in section 2.2, verifies the superiority of TTE as measure of firm-level exposure to the trade war.

We then evaluate the robustness of the results in Table 2 under several alternative specifications. First, we alter the continuous treatment difference-in-difference setting in equation (4) to a binary treatment setting. Specifically, we partition all firms to two categories by their average TTE before the trade war. Firms with $\overline{TTE_\iota}$ higher than median are classified as the treatment group and firms with $\overline{TTE_\iota}$ lower than median are the control group. Given this binary treatment, we re-estimate equation (4) and the results are shown in panel B. Similar as before, domestic market firms with above median TTE increase their sizes compared with their below median counterparts after the trade war, while having higher TTE causes negligible size changes for export-oriented firms. Second, we substitute baseline TTE with weighted TTE constructed using *word2vec* and run the regression in equation (4). Panel C in Table 3 depicts that using weighted TTE as the treatment variable still remains our baseline findings: the trade war has positive effect on domestic market firms while has no significant impact on export-oriented firms. Third, to check our results are robust against the choice of sample period, we restrict the sample to 2015-2019. Panel D illustrates this also does not change our results, both qualitatively and quantitatively.

Until now, in the difference-in-difference setting, we control for firm and time (year-quarter) fixed effects. However, the simple two-way fixed effects may omit confounding factors that also influence firm outcomes. For example, prevalent industry policies and region-specific policies will affect firm sales and costs, and they are not captured by firm and time fixed effects. Considering that, we additionally control for industry-year-quarter fixed effects and province-year-quarter fixed effects in Panel E. Similar as before, coefficients for domestic market firms are still significantly positive while coefficients for export-oriented firms are insignificant. Adding these fixed effects do not change our baseline findings.

Last but not least, we check that the growth of sales and costs for domestic market firms with higher TTE after the trade war are not driven by rise of product prices. This robustness check confirms that the trade war's effect on domestic market firm is not just nominal. In Table 3 panel F, firm's sales and costs are deflated by PPI (producer price index)[14], and these deflated firm outcomes are used as independent variable to estimate equation (4). After removing price factors, domestic market firms exposed to the trade war still experience increases of sales and costs, and the coefficients are quantitatively similar to those in Table 2. Then we can assert that increases in sales and costs for domestic market firms are at the quantity margin. Therefore, domestic market firms exposed to the trade war truly expand their sizes.

[Table 3 here]

4. Mechanisms

Previous section documents that, compared with no significant response of export oriented firms, domestic market firms exposed to the trade war unexpectedly expand after the trade war. It is then natural to ask what forces drive these results. To understand the mechanisms, we should explore what kinds of strategies firms apply to deal with the trade war. The most direct way to do that, is manually reading firm's information disclosure documents. However, this expert evaluation method has two apparent disadvantages: 1) Reading document by document is overwhelmingly time-consuming, especially for our large data sample; 2) Expert reading largely depends on the expert's own judgement, which makes the result difficult to replicate. Fortunately, the advancement in NLP provides us a suitable tool to tackle with these issues, namely LDA (latent Dirichlet allocation).

[14] PPI is at province-year-month level, and the base period is December 2020.

LDA is a Bayesian factor model for discrete data. It imagines a generative process that documents are represented as random mixtures over latent topics, and each topic is characterized by a distribution over all the words. Informally, each topic can be seen as a weighted word list that groups words expressing the same underlying theme. Specifically, for a corpus consisting of D documents each of length B_i, and V unique terms, the generative process is as follows: 1) Pick the number of topics, K; 2) Choose $\theta_i \sim Dir(\alpha)$, where θ_i is a vector representing the topic distribution of each document, and $Dir(\alpha)$ is a Dirichlet distribution with a symmetric parameter α; 2) Choose $\varphi_k \sim Dir(\beta)$, where φ_k is a vector representing the word distribution of each topic; 3) For the word position j in document i, choose a topic $z_{ij} \sim Multinomial(\theta_i)$, and choose a word $w_{ij} \sim Multinomial(\varphi_{z_{ij}})$[15]. After estimating a LDA model with topic number K, each document is reduced to a K-dimensional vector indicating its topic composition, and each topic can be interpreted by its word distribution.

For our purpose, LDA can help us automatically identify topics firms discuss to deal with the trade war, which is both time-efficient and reproducible. Now we briefly explain how to train the LDA in our application. First, for each trade term in each online earning conference document after 2018, we excerpt 20 words around it, and all these excerpts are used as the corpus. We limit the corpus to words in the neighbor of trade terms in documents after the trade war because, in these extracts, firms are most likely to discuss their tactics for dealing with the trade war. Given this corpus, we apply the R package *topicmodels* to estimate a LDA model with the number of topic $K = 10$[16]. After observing word distributions of these 10 topics, we find two topics reflecting firm's reaction towards the trade war. To visualize these two topics, we draw corresponding word clouds in Figure 4. Word clouds of other 8 topics are depicted in Appendix D1. In these word clouds, the size of a word representing its relative importance in a topic. We measure word's relative importance following the standard TF-IDF (term frequency-inverse document frequency) logic. Specifically, we calculate a word w's relative importance in topic k as $RI_k(w) = \varphi_k(w) \times \log(K / \sum_{k'} \varphi_{k'}(w))$, where $\varphi_k(w)$ is the probability of word w appearing in topic k. For a given topic, we assign high relative importance to the word which is very likely to appear in that topic (high TF), and has low probability of appearing in other topics (low IDF).

[Figure 4 here]

[15] Since Dirichlet distribution is the conjugate prior of multinomial distribution, LDA applies this distribution pair to simplify estimation.
[16] The results using other topic numbers are available upon request.

The topic in panel A has key words such as “supplier”(供应商), “purchase”(采购), “import substitution”(进口替代), “chip”(芯片), which correspond to supply chain adjustment. As a typical example of supply chain adjustment, Chinese chip industry has difficulties to import materials after the trade war, and leading companies such as Huawei resort to domestic suppliers such as SMIC. Firms adjusting their supply chains might be a possible mechanism to explain our empirical findings in section 3. After the trade war, export-oriented firms encounter with drastically increasing export and import tariffs, which hinder these firms from purchasing inputs overseas and/or selling products abroad. To tackle with the blockage of international supply chain, export-oriented firms may increase purchases from domestic suppliers and/or sales to domestic clients. As a result, domestic market firms connected with export-oriented firms through input-output linkages, obtain unexpected scale expansion.

In panel B, words such as “R&D”(研发), “intellectual property rights)”(知识产权), “innovation”(创新), “patent”(专利) are of high relative importance. Thus, this topic can be interpreted as firm’s innovation behavior. After the trade war, export-oriented firms might partly move their businesses back home, becoming potential competitors of domestic market firms operate in the same niche market. To escape from competition, these firms might exert additional efforts to innovate. Those succeed in innovation and upgrading their products might grasp higher demands and occupy larger market shares. However, since innovation takes a lot of time, this mechanism should have minor effects in the short run.

In sum, we apply the LDA model and find two possible mechanisms to explain the empirical results in the previous section. The supply chain adjustment channel argues that domestic market firms expand to accommodate to export-oriented firms which resort to local suppliers and/or clients after the trade war. The innovation channel conjectures domestic market firms benefit from innovation, so that they can escape competition brought by export-oriented firms which switch businesses back home[17]. Now we further exploit online earning conference documents to verify whether these mechanisms work.

4.1 Measuring Topic-Specific Trade Exposure

[17] As a complement to the LDA model, we explore which words are discussed more often after the trade war than before in appendix D2. Unsurprisingly, words related to supply chain adjustment and innovation are talked more frequently.

Following the logic in Hassan et al. (2019), we now illustrate how to measure firm-level trade exposure associated with specific topics. To achieve this goal, we first require training libraries $\boldsymbol{T}_s$ for specific topic s, containing the most related terms to that topic. Then for each online earning conference document, we calculate the topic s specific trade exposure as the share of co-occurrence of terms in $\boldsymbol{T}_s$ and terms in **T**:

$$TTE^s{}_{it} = \frac{\sum_b^{B_{it}} 1[b \in \boldsymbol{T}_s] \times 1[|b - \boldsymbol{t}| < 10]}{B_{it}}, \tag{5}$$

where $\boldsymbol{t}$ is the position of the nearest trade term in dictionary **T**. Intuitively, if a term related to a specific topic, e.g. supply chain adjustment, appears in the neighborhood of trade terms, then firms are very likely to discuss trade issues associated with this topic there. Thus, the share of co-occurrence can capture topic-specific trade exposure.

The measure of topic-specific trade exposure highly relies on the construction of training library $\boldsymbol{T}_s$. We follow the method used in Li et al. (2020) to build up $\boldsymbol{T}_s$. First, for a specific topic s, we choose several seed words clearly related to it. In the case of supply chain adjustment, “supply chain”(供应链), “supplier”(供应商), “client”(客户), “import substitution”(进口替代), are used as seed words. In the case of innovation, “R&D”(研发), “innovation”(创新), “IPR”(知识产权), “patent”(专利), are used as seed words. Second, we use *word2vec* to develop an expanded, context-specific dictionary for topic s. Specifically, we train the *word2vec* model on all online earning conference documents using the *genism* library in Python[18]. Given the trained model, we calculate the cosine similarity between each unique term in the corpus and the average of the seed words. Then we select the top 500 terms with the closest correlation, manually check all the words in the auto-generated dictionary, and exclude words that do not fit. Table D1 and D3 in Appendix D3 show dictionaries for supply chain adjustment and innovation.

Before testing the two channels, we here verify our topic-specific trade exposure measures correctly identify transcripts that feature significant discussions of trade issues related to specific topics. Table D2 shows the top ten online earning conference documents of the highest trade exposure associated with supply chain adjustment (henceforth as $\mathrm{TTE}^{\mathrm{SCA}}$). In these transcripts, firms truly talk about trade issues related to supply chain adjustment. For example, the second excerpt indicates that Huaji

[18] The dimension of word vectors is set to 300. Two words are seen as neighbors if they are no farther apart than five words. Words that appear fewer than five times in the corpus are omitted.

Dengyun, as an export-oriented firm, will resort to domestic clients to deal with the trade war. Besides direct reading of transcripts, we further verify the measure of TTE^{SCA} by demonstrating its relationship with measures of industry-level input-output linkages. Figure D3 indicates that TTE^{SCA} is positively correlated with industrial backward and forward linkages[19]. Intuitively, firms in industry with more input-output linkages are more susceptible to supply chain issues and tend to discuss supply chain adjustment more after the trade war. As for trade exposure related to innovation (henceforth as TTE^{Inno}), table D4 shows the top ten documents with highest TTE^{Inno}. A common topic in these excerpts is that in order to face market competition, firms conduct R&D investment and strive to develop technological advantages.

4.2 Supply Chain Adjustment or Innovation?

Given the measure of topic specific trade exposure, we now evaluate whether the supply chain adjustment and/or innovation channel can explain the scale expansion of domestic market firms exposed to the trade war. Specifically, we run the following difference-in-difference model:

$$y_{it} = \tilde{\theta}\overline{TTE_i^s} \times post_t + X_{it}'\Gamma + \alpha_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where y_{it} is the firm-level outcome of interest (log sales and costs); $\overline{TTE_i^s}$ is the firm-level average TTE^{SCA} or TTE^{Inno} before the trade war; $post_t$ is a dummy variable equals to 1 after the trade war (since 2018 quarter 1); X_{it} are firm controls including log firm asset and firm age; α_i and λ_t are firm fixed effects and time (year-quarter) fixed effects, respectively. Inferences are based on standard errors clustered at the firm level. The sample period is from 2011 to 2019.

Compared with the baseline regression in equation (4), the only difference in equation (6) is that, we substitute treatment variable from $\overline{TTE_i}$, i.e. firm's average TTE before the trade war, to $\overline{TTE_i^s}$, i.e. firm's average topic specific TTE before the trade war. Now we elaborate why this specification can identify the mechanism. As mentioned previously, TTE is assumed to be made up by two parts: one is load of the trade war's treatment dose, and the other is measurement error. Given this assumption of TTE's composition, together with the standard measurement error assumption, we show in appendix C1 that $\tilde{\theta} = \theta \times \bar{\beta} \times (1 - \frac{var(\overline{\eta_i})}{var(\overline{TTE_i})})$, where $\tilde{\theta}$ is the regression coefficient in equation (4), θ is the

[19] Industrial backward linkage is defined as $backward_{kt} = \sum_{j \neq k} a_{kj}$, where a_{kj} is the proportion of sector k's output supplied to sector j. Similarly, industrial forward linkage is defined as $forward_{kt} = \sum_{j \neq k} b_{kj}$, where b_{kj} is the share of inputs purchased by industry k from industry j in total inputs sourced by sector k.

trade war's treatment effect, $\bar{\beta}$ is TTE's load on the trade war, and $\frac{var(\overline{\eta_i})}{var(\overline{TTE_i})}$ is the variance ratio of measurement error. Following the same logic, we can similarly represent the coefficient $\tilde{\theta}$ in equation (6), only changing $\bar{\beta}$ to $\overline{\beta^s}$, i.e. the load of TTE^s on the trade war, and using corresponding variance ratio of measurement error. Clearly, if the load $\overline{\beta^s}$ is close to zero, then the regression coefficient will also be close to zero. Naturally, if the trade war affects firms through a mechanism s, then we will expect that mechanism-specific trade exposure TTE^s has large load on the trade war, i.e. large $\overline{\beta^s}$, which leads to significant $\tilde{\theta}$. On the contrary, if a mechanism does not hold, then its corresponding TTE^s has negligible load on the trade war, and the regression coefficient $\tilde{\theta}$ will be small and insignificant. In sum, the significance of regression coefficient in equation (6) can identify which mechanism works.

Table 4 shows the estimation results. In panel A, we test the supply chain adjustment mechanism. This mechanism argues that after the trade war, impacted export-oriented firms will switch their supply chain back home, and increase purchases (sales) from (to) domestic suppliers (clients). Therefore, domestic market firms connected with these export-oriented firms will experience scale expansion. If this mechanism works, we should have significantly positive coefficients of $\overline{TTE_i^{SCA}} \times post_t$ for domestic market firms. In line with our expectation, as documented in column (5) - (6), the $\tilde{\theta}$ coefficients are significantly greater than zero for domestic market firms. Specifically, a one standard deviation rise of TTE^{SCA} will lead to 5.9% and 5.1% growth of sales and costs for domestic market firms, respectively. On the other hand, since the trade war has no significant impacts on export-oriented firms in the baseline regression, unsurprisingly, the coefficients in column (3) - (4) are also negligible. Panel B lists regression results for the innovation mechanism. This mechanism states that since export-oriented firms might move their businesses back home, the competition faced by domestic market firms will intensify. To escape from competition, these firms might exert additional efforts to innovate, and those succeed in innovation and upgrading their products will earn larger market shares. As shown in column (3) - (4), for export-oriented firms, those with higher TTE^{Inno} experience marginal increase in total costs after the trade war while their sales stay constantly. However, the $\tilde{\theta}$ coefficients for domestic market firms in column (5) - (6) are insignificant, which implies the innovation mechanism cannot explain the scale expansion for domestic market firms. That is to say, results in panel B do not support the innovation mechanism. In sum, table 4 provides suggestive evidence only for the supply chain adjustment mechanism.

[Table 4 here]

Before showing more evidence for supply chain adjustment, we are curious about its dynamic effects on firm's sales and costs. We visualize the dynamic effects of two firm groups using a typical difference-in-difference event-study framework. Specifically, we estimate the following equation:

$$y_{it} = \overline{TTE_i^s} \times \sum_{\tau=-5}^{6} \tilde{\theta}_\tau I(t = t_0 + \tau) + X_{it}'\Gamma + \alpha_i + \lambda_t + \varepsilon_{it}, \tag{7}$$

Similar with equation (6), this specification includes firm controls such as log asset and age, and two-way fixed effects. Standard errors are clustered at firm level. Event time t_0 is assigned to be 2018 quarter 1. We bin event times ≥ 6 (after 2019 quarter 3) together and event times ≤ -5 (before 2016 quarter 4) together. Time -1 (2017 quarter 4) is chosen as the benchmark for comparison. The coefficients $\tilde{\theta}_\tau$ and their 95% confidence intervals are plotted in Figure 5.

[Figure 5 here]

In Figure 5, the top two and bottom two panels trace TTE^{SCA}'s impact on sales and costs for export-oriented firms and domestic market firms, respectively. Corresponding to Table 4, we document rising trends in sales and costs for domestic market firms exposed to the trade war, especially after 2019 quarter 1. One year after the trade war, domestic market firms with a standard deviation higher TTE^{SCA} will experience around 10% growth of sales and costs. Meanwhile, there are no significant impacts for export-oriented firms with higher TTE^{SCA}. Most panels in Figure 5 show insignificant $\tilde{\theta}_\tau$ before the trade war, which to some degree implies parallel trends between firms with high and low TTE^{SCA} before the trade war, and further mitigates endogeneity concerns for our regression specification. The event study graphs for TTE^{Inno} are displayed in Appendix D4. Corresponding with the results in table 4, TTE^{Inno} has no significant dynamic effects, further ruling out the innovation mechanism.

Now we provide more evidence supporting the supply chain adjustment mechanism. First, since supply chain adjustment will lead to scale expansion of domestic market firms connected with export-oriented firms through input-output linkages, we should expect those domestic market firms have positive sentiments towards supply chain adjustment topics. For instance, in the case study of Kaimeite Gases shown in table 1, this firm points out that after the trade war, the demand for domestic special gases will surge since importing such materials becomes difficult, and it is beneficial for Kaimeite itself. Thus, if the supply chain adjustment mechanism holds, we will see more optimistic sentiment for domestic market firms exposed to the trade war towards supply chain adjustment topics. To measure the topic specific sentiment, we refer to the method in Hassan et al. (2019), which is:

$$Sentiment^{s}{}_{it} = \frac{\sum_{b}^{B_{it}} 1[b \in \boldsymbol{T}_s] \times \sum_{c=b-10}^{b+10} S(c)}{B_{it}}, \tag{8}$$

where, as in equation (5), $\boldsymbol{T}_s$ is topic s specific dictionary, and $S(c)$ is the sentiment score for term c in the neighborhood of term b, which assigns a value of +1 if term c is associated with positive sentiment, a value of -1 if c is associated with negative sentiment, and 0 otherwise[20]. Intuitively, formula (8) captures sentiment around terms of a specific topic.

We standardize the measure of topic specific sentiment in equation (8) as the independent variable, and re-estimate equation (6), to see whether domestic market firms with higher TTE^{SCA} experience more positive sentiment towards supply chain adjustment. In this regression, we also control for firm-level discussion intensity of supply chain adjustment topic[21], since by construction, higher discussion intensity will lead to higher sentiment mechanically. Results are listed in table 5. Clearly, domestic market firms with higher TTE^{SCA} use more optimistic tones when discuss supply chain adjustment (column 7). Further, we decompose the sentiment index into positive and negative parts[22]. As shown in column (8) - (9), for domestic market firms, higher TTE^{SCA} means higher positive sentiment score after the trade war, while TTE^{SCA} has no significant impact on negative sentiment score. Table 5 manifests that domestic market firms exposed to the trade war are more optimistic towards supply chain adjustment issues, which additionally evidence the supply chain adjustment mechanism.

[Table 5 here]

To provide more direct evidence on the supply chain adjustment mechanism, we now utilize data of firm's suppliers and clients. Specifically, some listed firms report their purchases from top five suppliers and sales to top five clients in their annual reports. Given names of suppliers and clients, we can categorize them as domestic or foreign firms[23]. Based on that, we calculate export-oriented firms'

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[20] We construct dictionaries of positive and negative sentiment using *word2vec*. Specifically, after training the *word2vec* model over all online earning conference documents, we find words that have highest cosine similarities with "good" (利好), "good news" (好消息), "opportunity" (机会), "profit" (盈利) as the dictionary of positive sentiment, and words that have highest cosine similarities with "bad" (利空), "bad news" (坏消息), "unfavorable" (不利), "loss" (亏损) as the dictionary of negative sentiment. These two dictionaries are shown in Appendix D5.

[21] Specifically, firm-level discussion intensity of a topic is measured as $s_{it} = \frac{\sum_{b}^{B_{it}} 1[b \in \boldsymbol{T}_s]}{B_{it}}$.

[22] When we calculate positive sentiment, $S(c)$ assigns +1 to terms in the positive sentiment dictionary, and 0 otherwise. When we calculate negative sentiment, $S(c)$ assigns +1 to terms in the negative sentiment dictionary, and 0 otherwise.

[23] We classify a firm's suppliers and/or clients as foreign if these firms are located abroad.

purchases from domestic and foreign suppliers and sales to domestic and foreign clients, respectively[24]. These variables are then used as outcomes in regression a la equation (6), and results are summarized in table 6[25].

[Table 6 here]

If the supply chain adjustment mechanism holds, we would anticipate export-oriented firms exposed to the trade war increase their input purchases from domestic suppliers and/or enlarge their product sales to domestic clients. Consistent with such expectation, column (1) and (3) in table 6 indicate that, input purchases from domestic suppliers of export-oriented firms with higher TTE^{SCA} enormously increase after the trade war. On the other hand, the insignificant coefficients of sales to domestic clients for export-oriented firms with higher TTE^{SCA} suggest that, supply chain switches of these firms mainly happen upstream rather than downstream. This result also echoes with Jiao et al. (2020), which documents that Chinese exporters barely increase their domestic sales after the trade war. At last, foreign purchases and sales of export-oriented firms seem do not respond to the trade war. In sum, although limited by the sample size, results in table 6 convey direct messages supporting the supply chain adjustment mechanism.

Until now, we've focused on providing evidence for the supply chain adjustment mechanism. Here we turn to the innovation mechanism, and further confirm that this mechanism does not hold, at least in the short run. If the innovation mechanism is truly effective, then we should see domestic market firms with higher TTE^{Inno} conduct more R&D and hire more research employees. However, as shown in table 7, domestic market firms exposed to the trade war do not increase their R&D investment and hire more researchers. If anything, the number of researchers hired even slightly declines for domestic market firms with higher TTE^{Inno} after the trade war. Given results in table 7, complementary to those in table 4 panel B, we can assert that the innovation mechanism cannot explain the scale expansion of domestic market firms after the trade war.

[Table 7 here]

[24] Since firms only report the top 5 suppliers and clients, we can only calculate their domestic/foreign purchases and sales among their largest suppliers and clients. Although we cannot know firms' total domestic/foreign purchases and sales accurately, it is still possible to impute these variables. Given firms' total input purchases and product sales, and assuming shares of domestic/foreign purchases/sales among the top 5 suppliers/clients are the same as those among all suppliers/clients, we can impute firms' total domestic/foreign input purchases and product sales.

[25] As mentioned in Appendix A3, only a few listed firms disclose detailed information about their suppliers/clients such as firm names, which is indispensable to calculate domestic/foreign input purchases and product sales. Thus, the sample size in table 6 is much smaller than before.

4.3 Alternative: The Belt & Road Initiative

In the previous section, we've argued that the scale expansion of domestic market firms exposed to the trade war can be explained by the supply chain adjustment mechanism. The evidences we provide rely on the topic specific trade exposure, which, as a text based measure, might suffer from measurement error. Although our regression specifications in equation (4) and (6) have largely mitigated the endogeneity issue caused by measurement error, and are able to identify the sign of the trade war's treatment effect, there are still other concerns about measurement error. For example, in the meantime of the U.S.-China trade war, Chinese government also promotes the Belt & Road Initiative. Many listed firms respond to that initiative and expand their market in developing countries, which will lead to increases of sales and costs. If our TTE measure also contains discussion about the Belt & Road Initiative, then the estimated effect of the trade war will be contaminated. To mitigate this concern, we apply the following strategy. First, we construct the dictionary of the Belt & Road Initiative using *word2vec*; Specifically, we pick terms having highest cosine similarities with the seed word "the Belt & Road" (一带一路). Second, we construct trade exposure specific to the Belt & Road topic using formula (5), namely $TTE^{B\&R}$. Then we test $TTE^{B\&R}$'s impact on firm's sales and costs a la equation (6). If the Belt & Road Initiative truly affect previous empirical results, then we should see significant coefficients of $TTE^{B\&R}$. Fortunately, as shown in table 8, the coefficients of $TTE^{B\&R}$ are economically and statistically insignificant for both export-oriented firms and domestic market firms. That is to say, although the Belt & Road Initiative is a major policy at the same time of the trade war, it does not affect out empirical results.

[Table 8 here]

5. Conclusion

A rich literature has explored the impact of the U.S.-China trade war on firm behavior such as volume of exports and imports, investments, and employments, focusing on exporters and importers who are directly affected by the trade war. However, the trade war also has wide-spread indirect impacts: through supply chains, it can also influence domestic market firms, which is relatively less studied. In order to explore the trade war's overall effects on Chinese listed firms, especially on domestic market firms, this paper constructs a new measure, TTE, based on the discussion of trade related topics in online earning conference. We then validate that TTE truly captures firm's exposure to the trade war, by showing that it varies intuitively over time and across industries, and that it significantly affects the stock market performances of listed firms: in an event study framework, a one standard deviation higher TTE is associated with a 0.043 standard deviation decrease of firm's abnormal return immediately and a 0.021 standard deviation decrease of cumulative abnormal return during the first month of the trade war. We also illustrate that TTE has advantages over traditional exposure measure such as tariff exposure and TPU.

We then apply TTE to identify the sign of the trade war's treatment effect. While export-oriented firms exposed to the trade war have insignificant responses in sales and costs, domestic market firms with higher TTE experience scale expansion after the trade war. These somewhat surprising effects of the trade war on domestic market firms can be explained by the supply chain adjustment mechanism. After the trade war, export-oriented firms encountering blockage of international supply chain might transfer their supply chains back home. As a result, domestic market firms connected with these firms through input-output linkages, might have additional orders and obtain unexpected scale expansion. Utilizing documents of online earning conference, we build up topic-specific trade exposure measure, and provide evidence supporting the supply chain adjustment channel: Domestic market firms with higher TTE^{SCA} experience growth in sales and costs, and are more optimistic toward supply chain adjustment topics after the trade war. In addition, using data on firms' suppliers and clients from annual reports, we document that export-oriented firms exposed to the trade war increase their input purchases from domestic suppliers, further validating the supply chain adjustment channel.

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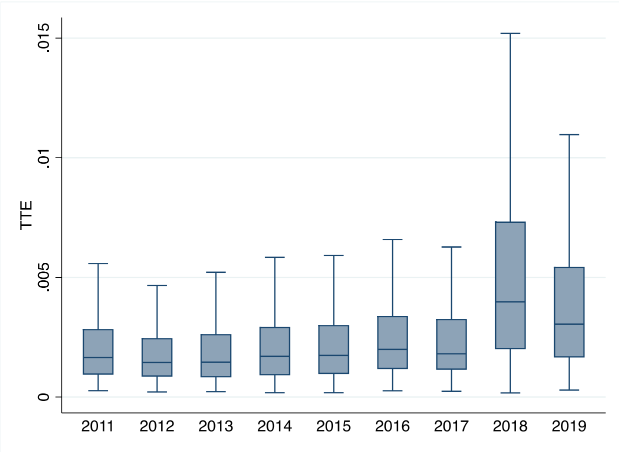
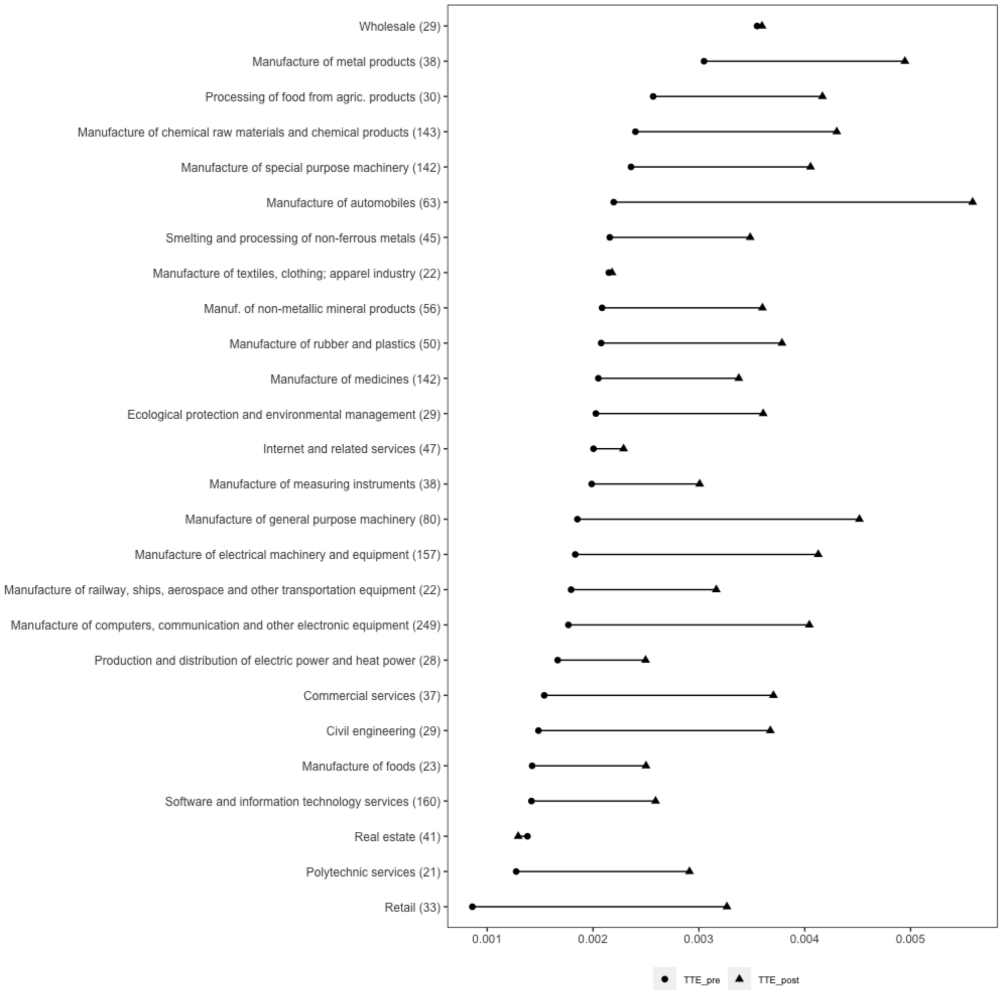
Figure 1: Descriptive Statistics of TTE

Panel A: TTE distribution over year



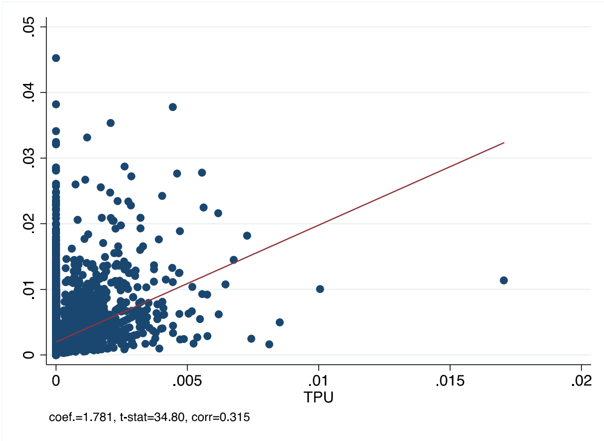
Panel B: TTE across industries



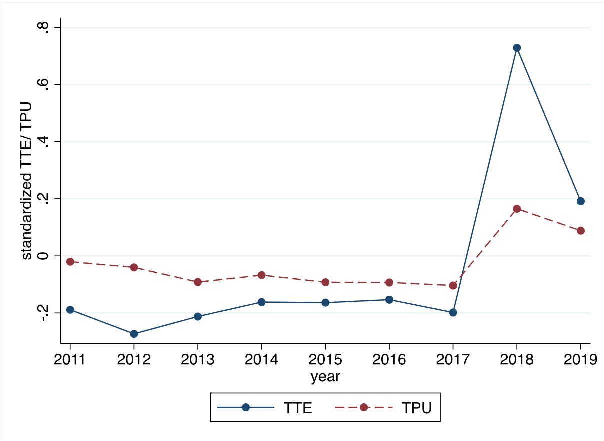
Notes: Panel A plots the distribution of non-zero TTE in each year during 2011-2019. The box plot shows the mean, 5th, 25th, 75th, and 95th percentiles of non-zero TTEs. Panel B plots the average TTE before and after the break of trade war in each industry with more than 20 listed firms, and the number of listed firms in each industry is in the parentheses. The triangles represent the average TTE before trade war in each industry while the circles represent the average TTE after trade war. Industries are ranked by their average TTE before the break of trade war.

Figure 2: TTE and TPU

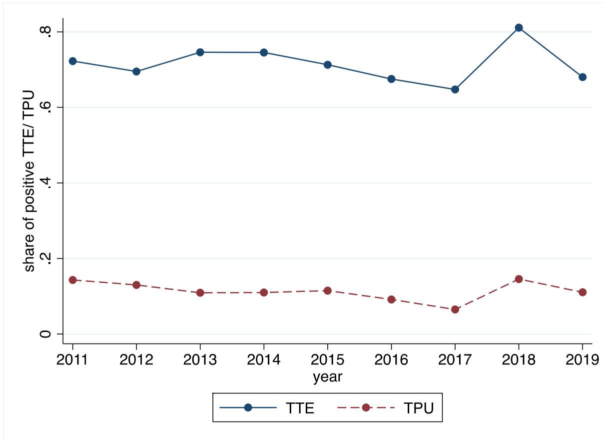
Panel A: Correlation between TTE and TPU



Panel B: Standardized TTE and TPU

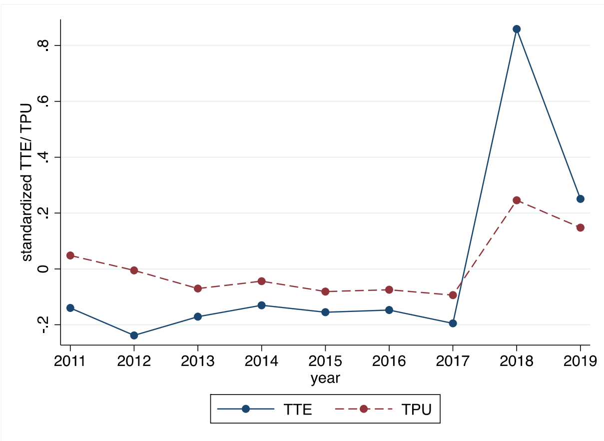


Panel C: Shares of non-zero TTE and TPU



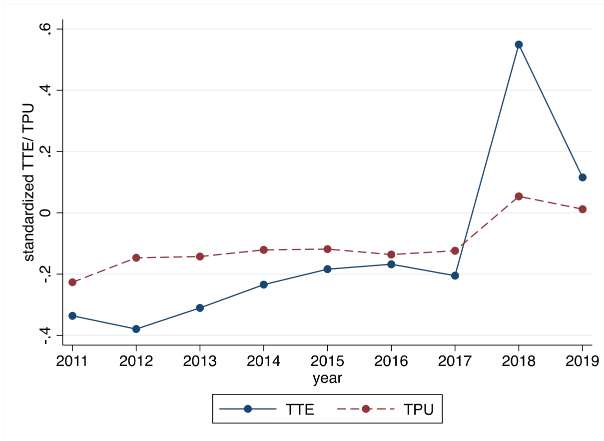
Panel D: Standardized TTE and TPU

Export-Oriented Firms



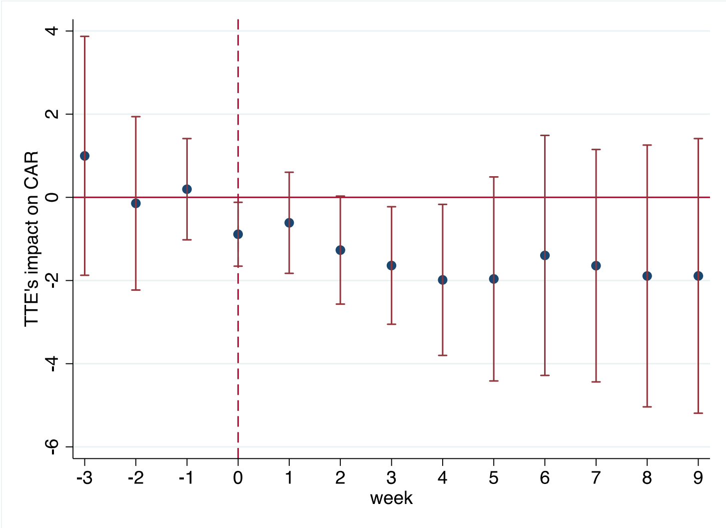
Panel E: Standardized TTE and TPU

Domestic Market Firms



Notes: Panel A plots the correlation between TTE and TPU. Panel B plots average standardized TTE and TPU over year. Panel C plots time trends of the shares of non-zero TTE and TPU. Panel D and E plot average standardized TTE and TPU over year across export-oriented firms and domestic market firms, respectively. Export-oriented firms are those who export or import once during 2011-2016. The remaining listed firms are classified as domestic market firms.

Figure 3: TTE's Impact on CAR in Different Time Windows



Notes: In this figure, we regress cumulative abnormal returns on TTE before the trade war across Chinese listed firms, controlling for log asset, firm age, and industry fixed effects. The standard errors are clustered at industry level. Each point and segment line stand for one regression in the corresponding time window. The coefficient and 95% confidence interval at week t ($-3 \leq t \leq 9$) shows the impact of TTE on cumulative abnormal returns in the time window [$|t|$ weeks before 2018/3/22, 2018/3/22] if $t < 0$, [2018/3/22, t weeks after 2018/3/22] if $t > 0$, and the abnormal return on 2018/3/22 if $t = 0$.

Figure 4: Two Channels as Word Clouds from the Topic Model

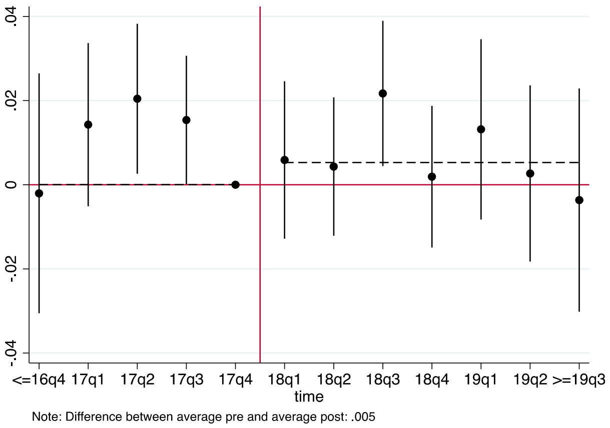
Panel A: Supply Chain Adjustment

Panel B: Innovation

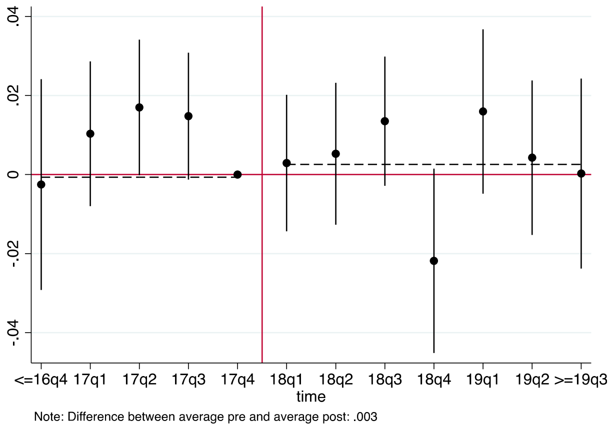
Notes: This table shows two topics about firm's response to the trade war. We excerpt 20 words around each trade term of each online earning conference transcript after 2018, and train a topic model based on this corpus. The trained topic model depicts two topics about firm's response to the trade war, namely supply chain adjustment and innovation. For each topic, we highlight the key words.

Figure 5: TTE^{SCA}'s Impacts on Sales and Costs, Event Study

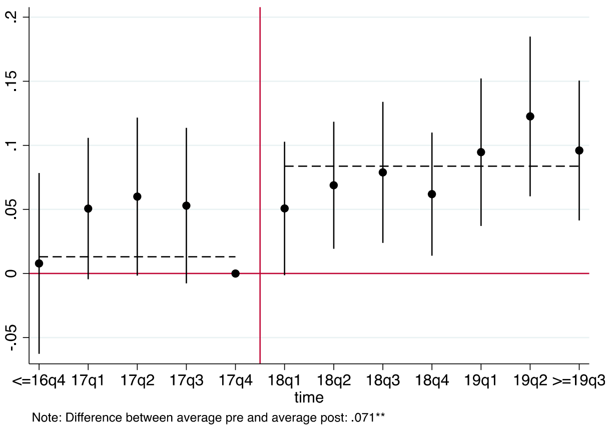
Panel A: log sales, export-oriented firms



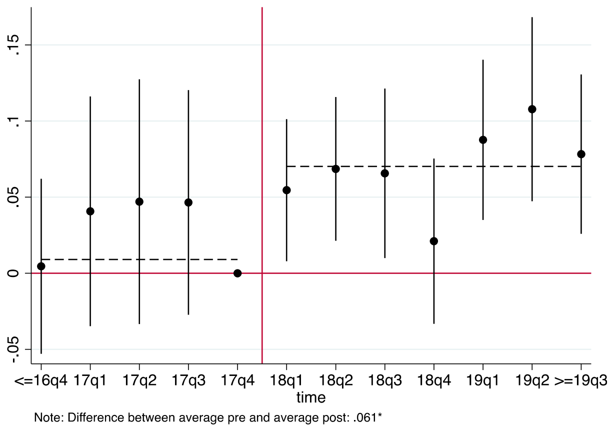
Panel B: log costs, export-oriented firms



Panel C: log sales, domestic market firms



Panel D: log costs, domestic-market firms



Notes: Figures plot coefficients and 95% CIs for interaction terms of TTE_i^{SCA} and each year-quarter dummy, in a standard difference-in-difference event study framework. Regressions control for log asset, age, firm and year-quarter fixed effects. Standard errors are clustered by firm.

Table 1: Case Studies

Panel A: Excerpts of 2018 Earning Conference of JinLaiTe Optoelectronics, an Export-Oriented Firm	
中美贸易摩擦，对公司出口业务有影响吗？	Will the US-China trade friction affect the company's export business?
对公司出口业务没有直接影响，公司很少出口到美国市场。间接影响为汇率，如果中美贸易摩擦升级为货币战，将对公司造成影响。原材料价格上涨，人工成本上涨，公司将从几方面处理：1、适当涨价；2、优化供应链体系；3、提升内部效率。	There is no direct impact on the company's export business, since the company rarely exports to the US market. The indirect impact is the exchange rate. If the US-China trade friction escalates into a currency war, it will have an impact on the company. The price of raw materials and labor costs have risen. The company will deal with it in several ways: 1. Appropriate price increases; 2. Optimizing the supply chain system; 3. Improving internal efficiency.
Panel B: Excerpts of 2018 Earning Conference of Kaimeite Gases, a Domestic Market Firm	
公司产品出口比例多少？主要有哪些海外市场？	What percentage of the company's products are exported? What are the main overseas markets?
您好，目前公司的产品只有干冰出口香港，其它产品都在国内进行销售，但是我们的电子特气产品出来后相信电子特气会在亚洲乃至全球具有影响力，因为这些气体是半导体、芯片产业的“血液”，其技术含量是非常高的，谢谢您的提问。	Hello, at present the company only exports dry ice to Hong Kong, and sells other products domestically. However, we believe our forthcoming products of electronic special gases will have influence in Asia and even the world, because these high-tech gases are crucial to the semiconductor and chip industry. Thank you for your question.
中美贸易战对公司有影响吗？	Will the US-China trade war impact the company?
你好！是的，中美贸易战给中国人在高科技，特别是半导体芯片产业方面提了一个非常重要的醒，因为中国在半导体芯片方面是非常弱的，生产半导体芯片的过程中所需的电子稀有气体几乎全靠进口，加之美国对中国商品惩罚性的关税，中国对美国进口产品关税的大幅提高，给了我们电子特气在国内生产一个非常好的机会，也就是说我们的这个产品出来后在国内不但可以填补国内的空白，而且还可以卖个非常好的价格。对我们盈利能力应该是个非常大的利好。谢谢！	Hi! Yes, the US-China trade war has brought a very important reminder to the Chinese in high technology, especially the semiconductor chip industry, because China is very weak in semiconductor chips, and the electronic gases required in producing semiconductor chips are almost entirely imported. China's substantial increase in tariffs on US imports has given us a very good opportunity to produce electronic special gases and to supply them to domestic markets. That is to say, our products can fill the domestic demand gap, and sell at very good prices. It should be beneficial to our profitability. Thanks!

Panel C: Management Discussion and Analysis in 2018 Annual Report of Hunan Kaimeite Gases

2018 年对中国经济来说是比较艰难的一年，全球经济新动能不足，发展不平衡、收入分配不平衡的问题加剧，新技术、新产业、新业态带来的新挑战凸现，各国政策内顾明显，国际贸易和投资壁垒不断提高。中美贸易摩擦、反全球化浪潮影响到中国出口业务；国内生态环境治理加强、人口红利退出人工成本增加，供给侧改革进一步深化这些都深刻影响到国内实体经济的生存与发展。2018 年湖南凯美特气体股份有限公司在公司董事会及管理层的领导下，通过管理团队及全体员工的共同努力抓住契机积极拓展市场，强化成本费用与安全生产管控，上下齐心协力认真贯彻落实年度经营计划，稳步推进各项工作计划有效实施。除长岭凯美特外，公司下设各分、子公司较好完成了年度预算经营目标，特别是湖南公司（特气分公司）、福建福源凯美特公司均超期完成利润指标。2018 年氧气和氮气市场形势好转，湖南特气产品销售数量与价格同步增加利润回报增厚。海南凯美特于 2017 年 4 月试车投产,2018 年全年正常生产。报告期内，公司实现营业收入 50,455.97 万元，比上年同期增长 17.81%；实现营业利润 10,718.38 万元，比上年同期增长 62.92%；归属于上市公司股东的净利润 9,385.41 万元，比上年同期增长 80.88%。	2018 is a relatively difficult year for the Chinese economy. The lack of new momentum in the global economy has intensified the problems of unbalanced development and income distribution. New challenges brought about by new technologies, new industries, and new formats have emerged. International trade and investment barriers continue to increase. US-China trade frictions and the wave of anti-globalization have affected China's export business; the strengthening of domestic ecological and environmental governance, the withdrawal of demographic dividends, the increase in labor costs, and the further deepening of supply-side reforms have profoundly affected the survival and development of the domestic real economy. In 2018, under the leadership of the company's board of directors and management, Hunan KMT Gas Co., Ltd. seized the opportunity to actively expand the market through the joint efforts of the management team and all employees, strengthened cost and production safety management and control, and worked together to earnestly implement Annual business plan, and steadily promote the effective implementation of various work plans. Except for Changling KMT, all branches and subsidiaries under the company have completed the annual budget and business objectives, especially Hunan Branch (Special Gas Branch) and Fujian Fuyuan KMT Company have exceeded their profit targets. In 2018, the oxygen and nitrogen market situation improved, and the sales volume and price of Hunan special gas products increased simultaneously, and the profit return increased. Hainan KMT was put into trial operation in April 2017 and will be in normal production throughout 2018. During the reporting period, the company achieved operating income of RMB 504.5597 million, an increase of 17.81% over the same period of the previous year; operating profit of RMB 107.1838 million, an increase of 62.92% over the same period of the previous year; net profit attributable to shareholders of listed companies was RMB 93.8541 million, an increase of 80.88% over the same period.

Table 2: TTE's Impacts on Sales and Costs

	All Firms		Export-Oriented Firms		Domestic Market Firms	
	Log Sales	Log Costs	Log Sales	Log Costs	Log Sales	Log Costs
	(1)	(2)	(3)	(4)	(5)	(6)
$TTE_i * post_t$	0.019	0.008	-0.015	-0.016	0.083***	0.057**
	(0.017)	(0.013)	(0.020)	(0.015)	(0.029)	(0.025)
Firm Control	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Quarter F.E.	Y	Y	Y	Y	Y	Y
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.365	0.385

Notes: This table shows TTE's impacts on list firms' sales and costs. Export-oriented firms are those who export or import at least once during 2011-2016. The remaining firms are classified as domestic market firms. TTE_i represents firm level average TTE before the trade war. We control for log firm asset, age, firm and year-quarter fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01

Table 3: TTE's Impacts on Sales and Costs, Robustness

	All Firms		Export-Oriented Firms		Domestic Market Firms	
	Log Sales	Log Costs	Log Sales	Log Costs	Log Sales	Log Costs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Control for TPU						
$TTE_i * post_t$	0.019	0.008	-0.015	-0.016	0.083***	0.056**
	(0.017)	(0.013)	(0.020)	(0.015)	(0.029)	(0.025)
TPU_{it}	-0.000	0.001	-0.002	0.000	0.005	0.006
	(0.006)	(0.004)	(0.006)	(0.004)	(0.010)	(0.009)
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.365	0.385
Panel B: DID with binary treatment						
$HighTTE_i * post_t$	0.064***	0.047**	0.019	0.018	0.153***	0.111***
	(0.024)	(0.020)	(0.027)	(0.024)	(0.044)	(0.037)
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.405	0.421	0.430	0.440	0.366	0.386
Panel C: DID with weighted TTE						
$TTEweight_i * post_t$	0.017	0.001	-0.012	-0.020	0.111***	0.079**
	(0.020)	(0.014)	(0.021)	(0.015)	(0.042)	(0.037)
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.365	0.385
Panel D: sample period from 2015 to 2019						
$TTE_i * post_t$	0.014	0.009	-0.013	-0.009	0.062**	0.038*
	(0.015)	(0.011)	(0.017)	(0.012)	(0.026)	(0.021)
Observations	25987	26019	17711	17733	8276	8286
Within R^2	0.314	0.324	0.339	0.348	0.277	0.284
Panel E: control for industry-year-quarter, and province-year-quarter fixed effects						
$TTE_i * post_t$	0.010	0.008	-0.021	-0.012	0.098**	0.074**
	(0.018)	(0.014)	(0.020)	(0.016)	(0.039)	(0.031)
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.398	0.411	0.422	0.435	0.360	0.377
Panel F: PPI deflated sales and costs						
$TTE_i * post_t$	0.018	0.007	-0.017	-0.018	0.085***	0.058**
	(0.017)	(0.013)	(0.020)	(0.015)	(0.029)	(0.025)
Observations	41831	41865	29162	29186	12669	12679
Within R^2	0.405	0.421	0.430	0.441	0.366	0.387

Notes: This table shows several robustness checks about TTE's impacts on firm sales and costs. In panel A, we control for firm-level TPU in addition. In panel B, $HighTTE_i$ represents for firms whose average TTE before the trade war are above median across all listed firms, and we use it as the treatment variable. In panel C, weighted TTE constructed using *word2vec* is used as the treatment variable. The sample period is from 2015 to 2019 in panel D. In Panel E, we additionally control for industry-year-quarter fixed effect and province-year-quarter fixed effects. Panel F shows TTE's impacts on PPI deflated sales and costs. Export-oriented firms are those who export or import at least once during 2011-2016. The remaining firms are classified as domestic market firms. In all six panels, we control for log firm asset, age, firm and year-quarter fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01

Table 4: Mechanism, Supply Chain Adjustment or Innovation

	Panel A: Supply Chain Adjustment					
	All Firms		Export-Oriented Firms		Domestic Market Firms	
	Log Sales	Log Costs	Log Sales	Log Costs	Log Sales	Log Costs
	(1)	(2)	(3)	(4)	(5)	(6)
$TTE_i^{SCA} * post_t$	0.016*	0.011	0.001	-0.000	0.059**	0.051**
	(0.009)	(0.008)	(0.010)	(0.008)	(0.025)	(0.025)
Firm Control	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Quarter F.E.	Y	Y	Y	Y	Y	Y
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.364	0.385

	Panel B: Innovation					
	All Firms		Export-Oriented Firms		Domestic Market Firms	
	Log Sales	Log Costs	Log Sales	Log Costs	Log Sales	Log Costs
	(1)	(2)	(3)	(4)	(5)	(6)
$TTE_i^{Inno} * post_t$	0.018	0.021*	0.009	0.019*	0.029	0.022
	(0.014)	(0.011)	(0.013)	(0.011)	(0.031)	(0.024)
Firm Control	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Quarter F.E.	Y	Y	Y	Y	Y	Y
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.363	0.384

Notes: Export-oriented firms are those who export or import at least once during 2011-2016. The remaining listed firms are classified as domestic market firms. TTE_i^{SCA} represents firm level average TTE^{SCA} before the trade war. TTE_i^{Inno} represents firm level average TTE^{Inno} before the trade war. We control for log firm asset, age, and firm and year-quarter fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01.

Table 5: TTE^{SCA}'s Impacts on supply chain adjustment sentiment

SCA	All Firms			Export-Oriented Firms			Domestic Market Firms		
Sentiment	overall	positive	negative	overall	positive	negative	overall	positive	negative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$TTE_i^{SCA} * post_t$	0.046	0.049	-0.053	0.028	0.038	-0.053	0.157*	0.116*	-0.094
	(0.037)	(0.046)	(0.044)	(0.043)	(0.057)	(0.033)	(0.095)	(0.063)	(0.187)
SCA_{it}	0.179***	0.190***	0.070***	0.159***	0.178***	0.089***	0.242***	0.226***	0.011
	(0.026)	(0.021)	(0.020)	(0.027)	(0.023)	(0.025)	(0.066)	(0.049)	(0.030)
Firm Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10494	10494	10494	7310	7310	7310	3184	3184	3184
Within R^2	0.019	0.022	0.004	0.015	0.019	0.005	0.039	0.036	0.003

Notes: This table shows TTE's impacts on firm's sentiments towards supply chain adjustment topic. Export-oriented firms are those who export or import at least once during 2011-2016. The remaining listed firms are classified as domestic market firms. TTE_i^{SCA} represents firm level average TTE^{SCA} before the trade war. SCA_{it} is the discussion intensity of supply chain adjustment. We control for log firm asset, age, firm and year fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01.

Table 6: TTE^{SCA}'s Impact on Top5 Suppliers and Clients

	Export-Oriented Firms							
	Log Purchase from Suppliers				Log Sales to Clients			
	Top5		Imputed All		Top5		Imputed All	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TTE_i * post_t$	0.864*	-0.016	0.959*	0.015	0.867	0.017	0.836	0.004
	(0.478)	(0.809)	(0.499)	(0.846)	(0.780)	(0.706)	(0.807)	(0.765)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Observations	0.022	0.000	0.026	0.000	0.029	0.002	0.031	0.002
Within R^2	0.019	0.002	0.022	0.002	0.024	0.002	0.026	0.002

Notes: This table shows the effects of TTE^{SCA} on export-oriented firms' purchases from suppliers and sales to clients. Export-oriented firms are those who export or import at least once during 2011-2016. TTE_i represents firm level average TTE before the trade war. We calculate firm's purchases and sales among domestic and foreign top 5 suppliers and clients from annual reports. Given firms' total input purchases and product sales, and assuming shares of domestic purchases/sales among the top 5 suppliers/clients are the same as those among all suppliers/clients, we impute firms' total domestic input purchases and product sales. Similarly, we calculate imputed total purchases from foreign suppliers and sales to foreign clients. We control for log firm asset, age, firm fixed effects, and year fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01.

Table 7: TTE^{Inno}'s Impact on Innovation

	All Firms		Export-Oriented Firms		Domestic Market Firms	
Log R&D	Investment	Worker	Investment	Worker	Investment	Worker
	(1)	(2)	(3)	(4)	(5)	(6)
$TTE_i^{Inno} * post_t$	-0.006	-0.008	0.009	0.009	-0.030	-0.036*
	(0.014)	(0.012)	(0.019)	(0.014)	(0.024)	(0.021)
Firm Control	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Observations	9680	6100	7072	4352	2608	1748
Within R^2	0.279	0.242	0.300	0.249	0.232	0.232

Notes: This table shows TTE^{Inno}'s impact on firm's R&D behavior. Export-oriented firms are those who export or import at least once during 2011-2016. The remaining listed firms are classified as domestic market firms. TTE_i^{Inno} represents firm level average TTE^{Inno} before the trade war. We control for log firm asset, age, and firm and year fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01.

Table 8: Alternative Mechanism, the Effect of the Belt and Road Initiative

	All Firms		Export-Oriented Firms		Domestic Market Firms	
	Log Sales	Log Costs	Log Sales	Log Costs	Log Sales	Log Costs
	(1)	(2)	(3)	(4)	(5)	(6)
$TTE_i^{B\&R} * post_t$	0.010	-0.001	0.010	-0.000	0.010	-0.001
	(0.011)	(0.010)	(0.019)	(0.017)	(0.009)	(0.008)
Firm Control	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Quarter F.E.	Y	Y	Y	Y	Y	Y
Observations	41915	41949	29198	29222	12717	12727
Within R^2	0.404	0.420	0.430	0.440	0.363	0.384

Notes: Export-oriented firms are those who export or import at least once during 2011-2016. The remaining listed firms are classified as domestic market firms. $TTE_i^{B\&R}$ represents firm level average $TTE^{B\&R}$ before the trade war. We control for log firm asset, age, and firm and year-quarter fixed effects. Standard errors are clustered at firm level. *p<0.1, **p<0.05, ***p<0.01