STOCK MARKET REACTIONS AND TRADE EXPOSURE AROUND THE WORLD: EVIDENCE FROM THE US-CHINA TRADE WAR

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Master thesis

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Abstract

This thesis aims to investigate the stock market reactions around the world to the US-China trade war using an event study. Specifically, we study abnormal returns and abnormal volatility on March 22, 2018, when the first tariff measures focused on China were debated in the US. Then, consistent with some theoretical models, we check the heterogeneity of the results according to specific firm characteristics. The most affected stocks were those of China, the US, and Asia. Size and trade exposure are related to lower abnormal returns and higher abnormal volatility, while productivity is related to higher returns and lower volatility. Finally, price reactions are used to measure exposure to the trade war and as explanatory variables over financial outcomes in the following years using a difference-in-differences approach. Firms that experienced lower abnormal returns showed a reduction in sales, employment, and capital growth. For abnormal volatility, the direction is the opposite, and it is significant. When we split the samples by firm characteristics, the effects are mainly present in firms that are larger, more productive, and more exposed to trade. Results have implications for policymakers regarding employment, managers in firm decisions, and investors in forecasting and risk management.

Keywords: Heterogeneous firms, US-China trade war, Abnormal volatility, Abnormal returns

1 Introduction

Trade policies -both liberalization and implementation of trade barriers- affect several firms' decisions and outcomes because of globalization. An example of the relevance of this issue can be seen in the way the market reacted to the US-China trade tensions considering that they are the leading product importers and exporters in the world. Specifically, the tariff announcement by the US on March 22, 2018, was the first of a long series of direct tariff impositions between China and the US. According to the US, the justification for the request for tariffs, with an ex-ante value of approximately US$60 billion, was the unfair business behavior of China (Egger & Zhu, 2021).[1] As it is known, the tensions between these two countries keep occurring, generating an increase in the trade policy uncertainty that affects many countries (Carballo et al., 2018; Fajgelbaum & Khandelwal, 2021). The impacts of the trade war on firms' present value of output disruptions may be reflected in stock prices, serving as an early indicator for policymakers, managers, and investors (Carlomagno & Albagli, 2022; Greenland et al., 2020).

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[1]This thesis focuses on this event, considering that the US tariff impositions on solar panels and washing machines in January 2018 were not targeting China directly. Moreover, on March 01, 2018, the US imposed tariffs on steel and aluminum, which affected mainly other countries rather than China (Bown, 2018). Therefore, as the discussion held by the government on March 22 was focused on targeting China directly, it has been considered the beginning of the trade war (Egger & Zhu, 2021; Gu et al., 2021; Xu et al., 2021), even if the official document was published days after.

The literature has shown that firm size, productivity, trade exposure, industry, and geographic location determine how the earnings expectations will react in a heterogeneous way to some trade policy (Antràs et al., 2017; Breinlich, 2014; Chaney, 2008; Greenland et al., 2020). Moreover, these factors also determine how trade policies are related to the volatility of earnings and output (Di Giovanni & Levchenko, 2009; Vannoorenberghe, 2012; Vannoorenberghe et al., 2016). Given that earnings expectation and volatility change, financial markets should reflect on the stock returns and volatility (Beaver, 1968; Kondor, 2012). The fact that stock reactions reflect the average consensus of the market in a high frequency and firm-level aspect makes it a straightforward way to capture policy effects on heterogeneous firms. These effects are difficult to quantify with standard measures, and the reaction can be used to measure trade exposure (Greenland et al., 2020).

Above all, the literature has focused on abnormal stock returns as the dependent variable (Amiti et al., 2021; Breinlich, 2014; Egger & Zhu, 2021; Gu et al., 2021; Qin et al., 2022; Wang et al., 2020; Xu et al., 2021). However, there are other variables representing higher-order moments, such as abnormal volatility, that may serve as an indicator to complement abnormal return on testing exposure to a specific event (Balaban & Constantinou, 2006; Beaver et al., 2020; Chortareas et al., 2012; Essaddam & Karagianis, 2014; Hao et al., 2021; Kondor, 2012; Landsman & Maydew, 2002; Lozada et al., 2021; Prasad et al., 2021). In particular, Cready and Hurtt (2002) and Kondor (2012) show that before stating that an event did not disclose new information, investors should look at other trading-based variables, such as volatility and volume.[2] Finally, Greenland et al. (2020) show that abnormal stock reactions may be used as right-hand variables to test the exposure to changes in trade policies and, therefore, to analyze the medium-term effects on financial outcomes. If the relationship is significant, it means that the market appropriately gathers information about the impact of the tariffs on firms and that this information is helpful as a predictor for future results.

In line with the above, the present study seeks to contribute to the literature on international finance in three ways. First, it gives empirical evidence of the heterogeneous effects of the US-China trade war on firms, expanding the analysis from the US and China to the entire world. In particular, we are focused on Breinlich's (2014) model predictions. Second, it complements the literature on the US-China trade war by analyzing abnormal returns and abnormal volatility during the events, allowing policymakers, managers, and investors to have information over the first and second moments of the indicator. Third, we extend the usual event study methodology in the US-China trade war literature by employing the differences-in-differences (DiD) procedure by Greenland et al. (2020). This method uses stock market reactions as indicators (right-hand variables) to identify exposure to trade policy and the medium-term effect on financial outcomes. For the empirical application, we use a firm-level data set of financial and trade statistics, industry data, geographic information, and stock prices for over 18,000 companies in more than 40 countries. We build

[2]As the Section 3 shows, our volatility measure is based on returns, but there are other measures based on high and low daily prices which have different information from returns, see e.g. Yang and Zhang (2000).

our analyses based on the trade announcement made by the United States on March 22, 2018.

The results show that larger companies experienced more abnormal volatility and lower abnormal returns during the event day. According to the theoretical predictions, it can be explained by the fact that these firms have more access to international markets and more liquidity in stock markets. Productivity shows a negative relation with volatility and positive relation with returns, suggesting that more productive firms suffer the least after the tariff policy. Trade exposure is also a factor of higher volatility and negative abnormal returns. According to the DiD estimations, the results state that when we use abnormal volatility and abnormal return as explanatory variables, they generally work as a measure of trade exposure and may be used as a predictor for sales, employment, and capital growth in the years after the announcement. Specifically, firms that experienced lower abnormal returns showed a reduction in sales, employment, intangibles and capital growth. For abnormal volatility, the direction is the opposite, and it is significant. When we split the samples by firm characteristics, the effects are mainly present in larger, more productive firms and those more exposed to trade.

Estimation results have several implications for policymakers, managers, and investors. In general, markets suffered drops in prices and higher risk during the announcement day. Considering that the tariffs influence earnings and other financial variables, such as investment decisions (Gutiérrez & Philippon, 2017; Khandelwal, 2010), estimations suggest that investors discount the future expected results in the current price. Thus, the market identifies which firms may suffer the most due to the policy. Managers and investors can use the abnormal volatility and abnormal return as an indicator to improve financial forecasts (e.g., profits and investments) for each company. Given that the US-China trade war has been a constant conflict in the last years and trade disputes may be used as a political strategy (Conconi et al., 2017), these indicators can be employed to adjust investment and firm decisions in future events (Mullainathan, 2002). Finally, our results are interesting for policymakers because the indicators show that the policy of higher tariffs is related to a fall in employment growth within firms, as the theories suggest.

The remainder of this paper proceeds as follows. Section 2 discusses the related literature and the hypothesis development. In Section 3, we explain the methodology and the variables used. Section 4 discusses the results, and Section 5 summarizes the main conclusions.

2 Related Literature and and hypotheses development

This section reviews the theory and some empirical work related to the paper. First, we explain the connection between stock prices and the tariff trade policy and then develop the hypotheses of heterogeneous reactions and the ones linking stock prices with future financial outcomes.

According to the dividend discount model, the price of a stock can be represented by the present value of future dividends (Berk & DeMarzo, 2007). If it is assumed that firms distribute all the profits as dividends, as Breinlich (2014) does, we have the link between price and future expected profits. Moreover, if the variance of expected profits is affected, so is the variance of price. To see this, Beaver (1968) states that in the presence of uncertainty, the price change is a realization from a probability distribution of investors' reasoning of what is the fair price, so the variance in a given period will increase proportionally to the transactions made. Moreover, according to the microeconomic model of asset pricing, changes in stock prices are affected by changes in the expectation and volatility of dividends, the marginal utility of consumption, and some correlations. Therefore, if we assume that markets are informationally efficient, the change in expected profits and other financial variables will be captured by the current price (Breinlich, 2014; Greenland et al., 2020) and current volatility (Beaver, 1968).

Since the stock market data are at the firm level, heterogeneous firm models of international trade can be tested directly. Breinlich (2014) presents a theoretical model of firm reactions to trade policies. He tests it using stock market data, finding a direct relationship between abnormal price reactions and firm characteristics representing size and trade exposure. This can be explained by large firms having the most access to international markets (Breinlich, 2014; Chaney, 2008; Melitz, 2003). Moreover, larger firms have more access to stock markets and present more liquidity (Merton, 1987), and therefore there are more investors and information on price and volatility.

Heterogeneous firm models also address productivity. Chaney (2008) and Melitz (2003) present a framework in which trade policies are exploited to a greater extent by more productive firms. However, these models focus on trade liberalization, whereas in this paper, we focus on increasing tariffs and thus reducing market participants. There may also be a relationship between productivity and market concentration, as Autor et al. (2020) document how, in the US, more productive firms take a larger market share, increasing the concentration of sales in a small number of firms. Thus, given that after the imposition of the tariff analyzed in this article, the number of participants would be reduced, the most productive firms would be the most likely to take this as an advantage. In the same vein, Breinlich (2014) argues that the least productive firms suffer the most in their profits. In his paper, a distinction is made between exporters and non-exporters, which makes it difficult for us to test, but it is possible to separate the effects with our proxies.

Finally, trade exposure is a crucial factor in heterogeneous firm models. Breinlich's (2014) theoretical model is based on Chaney's (2008) model where firms sell differentiated products, and the profits of firm i selling in market j are constrained by market tariffs. A tariff reduction increases the earnings of firms with more trade exposure. In this case, the policy directly affects two groups: importers to the US and exporters from China. These groups will experience heterogeneous effects depending on the substitution effect (Chaney, 2008). Di Giovanni and Levchenko (2009) relate trade openness to output volatility, similar to Vannoorenberghe (2012), who finds that, at the firm level, firms more open to trade have more volatile sales.

In line with the theoretical and empirical literature presented, we formally test the following hypotheses:

> **H1:** Bigger firms experience more negative abnormal returns and higher abnormal volatility on the day of the tariff increase announcement, mainly due to greater access to international markets and stock markets.
>
> **H2:** Less productive firms experience more negative abnormal returns and higher abnormal volatility on the day of the tariff increase announcement.
>
> **H3a:** Firms with trade exposure in the same product lines where China is the leading exporter suffer more negative abnormal returns, and higher abnormal volatility as tariffs imposed by the policy may affect them.
>
> **H3b:** Due to the substitution effect, companies with trade exposure in the same product lines for which the US is the major importer will benefit from becoming potential new partners and therefore experience higher abnormal returns and lower abnormal volatility.

In addition to studying the determinants of price reactions, Greenland et al. (2020) propose using them as right-hand variables. The goal is to use the "wisdom of the crowds" to predict and understand subsequent firm outcomes after a trade policy, which complements the previous literature on indicators for trade exposure (Amiti & Konings, 2007; Fisman & Zitzewitz, 2019). Previously, this method was used in the context of patents following Schumpeterian predictions (Kogan et al., 2017). The logic behind this method is that, according to the dividend discount model, the market does a good job of incorporating the information efficiently into the current price. If this is true, the abnormal return and the abnormal volatility have explanatory and predictive power in future financial outcomes, which we will explain below.

In Breinlich's (2014) model, a tariff reduction may increase firms' sales with more trade exposure and larger size. The counterpart with an increase in tariffs would be to find a negative relation with profits for larger firms. After defining the theoretical model, he provides evidence using abnormal returns as an indicator for the US and Canadian markets.

Literature also investigates the relationship between assets' reactions to production inputs -capital and employment- following tariff increases. Studies have shown that increased regulations have generated a fall in capital investment via decreased competition (Gutiérrez & Philippon, 2017). Also, higher product quality is related to increased market competition incentivizing capital investment (Khandelwal, 2010). Similarly, labor share may be reduced in industries with higher concentrations (Autor et al., 2020). In his work, Greenland et al. (2020) show a positive relationship between abnormal returns of goods producers and service firms and a higher probability of survival, profits, capital, and employment in the following six years.

Assuming information efficiency in the market and the literature behind the relation between financial decisions and trade liberalization, we design our fourth group of hypotheses:

> **H4:** There is a direct (inverse) relationship between abnormal returns (abnormal volatility) suffered on the announcement day and the growth in sales, employment, intangible assets, and capital in the following years.

The following section explains the methodology used to test the hypotheses.

3 Methodology

The event-study methodology allows us to test the stock market reactions specific announcements. The literature has focused mainly on studying abnormal returns (Amiti et al., 2021; Breinlich, 2014; Egger & Zhu, 2021; Gu et al., 2021; Qin et al., 2022; Wang et al., 2020; Xu et al., 2021). In this paper, we estimate the abnormal returns following the standard approach, which uses the market model to build the counterfactual of returns during the event given a set of information and an estimation window (Binder, 1998; Campbell et al., 1998; Lintner, 1965; Sharpe, 1964). The event day is defined as March 22, 2018, when the US explicitly announced the first tariff on Chinese products. This event is regularly used in the literature to study the US-China trade war, as it is the date that brings the surprise news (Egger & Zhu, 2021; Gu et al., 2021; Xu et al., 2021). Following Binder (1998), we set the estimation window to be the returns data of the year before the event, in this case, 2017.[3] Thus, for the pre-announcement period, we estimate by OLS the model,

$$R_{it} = \alpha_i + \beta_i R_{it}^M + \epsilon_{it} \qquad \forall i = 1, 2, ..., N \qquad \forall t = 1, 2, ..., t*, \tag{1}$$

with $t*$ being the last day of the estimation window. $R_{i,t}$ is the daily log return for each stock i, $R_{i,t}^M$ is the daily log return of the market index for the country of stock i, and $\epsilon_{i,t}$ is the error term. After computing the regression, we use the estimated parameters to calculate the abnormal returns during the event day as follows:

$$AR_i = R_i - (\hat{\alpha}_i + \hat{\beta}_i R_i^M) \qquad \forall i = 1, 2, ..., N, \tag{2}$$

However, higher moments also experience abnormal reactions during events. The article's objective is to analyze both abnormal returns and abnormal volatilities. Following Beaver (1968) and Landsman and Maydew (2002), we use the following formula as the measure for abnormal volatility during the event day:

$$AVOL_i = \frac{AR_i^2}{\sigma_i^2} \qquad \forall i = 1, 2, ..., N, \tag{3}$$

where a value between zero and one indicates a smaller than normal volatility, and when $AVOL$ is greater than one, it means higher than normal volatility. Equation (3) does not assume any specific way to compute the variance in the denominator. Thus, because of the stylized facts of stock returns, we estimate a GARCH (1,1) model (Bollerslev, 1986) to consider the time-varying dynamics of volatility.[4] Specifically, we define the following equations for the GARCH model:

$$R_{it} = \alpha_i + \beta_i R_{it}^M + \epsilon_{it}, \tag{4}$$

$$\sigma_{it}^2 = c_i + a_i \epsilon_{it}^2 + b_i \sigma_{it-1}^2, \tag{5}$$

$$\epsilon_{it} = \eta_{it}\sigma_{it}, \quad \eta_{it} \sim N(0, 1) \qquad \forall i = 1, 2, ..., N \qquad \forall t = 1, 2, ..., t*,$$

[3] We also tested different windows for robustness, and the results don't change.

[4] We use the order (1,1) for the process as Pakel et al. (2020) and Berben and Jansen (2009) argue that the choice of the univariate GARCH model is of minor relevance and that the (1,1) process succeeds in capturing adequately the persistence in second moments of high-frequency asset returns.

where c_i, a_i and b_i are the parameters of a GARCH(1,1) process for each stock, and $t*$ denotes the last day of the estimation window. With the mean equation (4) we control for the systematic dynamics by saying that the return follows the market model. However, as Greenland et al. (2020) clarify, estimating both returns and volatilities for each firm individually omits the possible effect of other systematic risks, such as changes in interest rates and aggregate prices. Therefore, the results may be considered carefully.

We estimate the process by maximum likelihood. Given that we have information until the estimation window finishes Ω_t*, the k^{th} forward forecast using the GARCH model is:

$$E[\sigma_{i,t*+h}|\Omega_t*] = \hat{c}_i \sum_{j=0}^{h-1}(\hat{a}_i + \hat{b}_i)^j + (\hat{a}_i + \hat{b}_i)^{h-1}\hat{a}_i\hat{\epsilon}^2_{i,t*} + (\hat{a}_i + \hat{b}_i)^{h-1}\hat{b}_i\sigma_{i,t*}, \tag{6}$$

where the hat represents the estimated parameters of equation (5). The estimation window for the GARCH model is $[t-510, t-10]$, being t the event day.[5]

After finding $AVOL$ and AR for each stock, the next step is to regress them over the firm characteristics that, according to the hypotheses, are determinants of the expected future earnings and, therefore, the current stock price. This is the procedure commonly used in the literature to test heterogeneous firm-level responses to a particular event using the stock return (Breinlich, 2014; Forbes, 2004; Greenland et al., 2020). In this paper, we analyze not only the determinants of abnormal returns but also abnormal volatility.

According to our hypotheses, we regress the abnormal stock reactions over firm variables representing size, productivity, and trade exposure. Specifically, the firm's size is represented by the logarithm of the sales. The logarithm of the sales to working capital ratio is used to measure productivity. Finally, we use two dummy variables explained in detail in the next section for trade exposure. We estimate the following OLS regressions:

$$AVOL_i = \beta_0 + \beta_1 \text{Size}_i + \beta_2 \text{Productivity}_i + \beta_3 \text{ImportsUS}_i + \beta_4 \text{ExportsChina}_i + \gamma \boldsymbol{X_i} + \alpha_g + \epsilon_i, \tag{7}$$

$$AR_i = \beta_0 + \beta_1 \text{Size}_i + \beta_2 \text{Productivity}_i + \beta_3 \text{ImportsUS}_i + \beta_4 \text{ExportsChina}_i + \gamma \boldsymbol{X_i} + \alpha_g + \epsilon_i, \tag{8}$$

where $AVOL$ and AR are the abnormal volatility and abnormal returns defined in equations (3) and (2), and $\boldsymbol{X_i}$ represents the vector of winsorized control variables in 2017, the year before the trade war analyzed started, described in Table A.2 in the appendix. The two last terms of each equation are the industry fixed effects and the error term. We use industry fixed effects because an industry trend may guide the results. NAICS 4-digit codes are used as the industry fixed effects to avoid multicollinearity problems because the variables ImportsUS_i and ExportsChina_i are calculated based on the NAICS 6-digit codes. Finally, the cross-correlation of the error terms may be different from zero, i.e., for two firms i and j, $E(\epsilon_i'\epsilon_j) \neq 0$, and thus the standard errors are not consistent and efficient. Standard errors are clustered at the NAICS 6-digit code level to deal with this problem. The coefficients of interest are $\beta_1, \beta_2, \beta_3$, and β_4, which the sign may vary according to each specific hypothesis

[5] As robustness exercise, we also estimate the results using the daily historical variance over 2017 as a measure for σ_i^2, and the results remain similar, as shown in the appendix.

and the selected sample in the results.

Finally, the paper evaluates if the investors can make decisions during the announcement anticipating possible outcomes in the future firm results. In other words, we use DiD OLS panel regressions, following Greenland et al. (2020), to test whether the abnormal return and abnormal volatility experienced during the event day may work as an indicator or predictor for future behavior of financial variables. It does not mean that the abnormal return and volatility affect firms directly, but it suggests that investors anticipate the effects of the trade policy on firms. The models are the following:

$$y_{it} = \delta \,\mathrm{Post}{*}AVOL_i + \gamma \,\mathrm{Post}{*}\boldsymbol{X_i} + \alpha_i + \alpha_t + \epsilon_{it} \tag{9}$$

$$y_{it} = \delta \,\mathrm{Post}{*}AR_i + \gamma \,\mathrm{Post}{*}\boldsymbol{X_i} + \alpha_i + \alpha_t + \epsilon_{it}, \tag{10}$$

where y_{it} is the financial outcome of interest, i.e. $y_{it} \in \{\Delta \log(Sales)_{it}, \Delta \log(Employees)_{it}$, $\Delta \log(Intangibles)_{it}$, $\Delta \log(Total\,Capital)_{it}\}$. $AVOL_i$ and AR_i are the stock markets reactions defined in equations (3) and (2). δ is the DiD term of interest, and Post is a dummy variable scoring 1 for the years after the event date, i.e., 2018 and 2019. $\boldsymbol{X_i}$ represents the vector of winsorized control variables that may influence the financial variables through channels unrelated to the trade war (i.e. controls in 2017, before the event date). α_i describes firm fixed effects, which capture each firm's time-invariant idiosyncratic characteristics. α_t represents the time fixed effects that affect all firms. The standard errors are clustered at the sector level.

4 Data

We use stock market data for all the countries that appear in the Asian Development Bank multi-region input-output database, covering almost all of the world. For each stock, we download from Datastream the daily closing price in US dollars, and we compute the return as $\ln P_t - \ln P_{t-1}$. We followed a static screen process based on Hanauer and Lauterbach (2019) and Forbes (2004). First, a filter is made to avoid downloading data for equity investment instruments, non-equity investment instruments, and companies with sector "Unclassified." We selected the stocks listed in the main(s) local stock exchange and the local currency for each country. Every stock should have data for the estimating windows used and the event day. We also deleted data for those countries with less than ten firms. Finally, following Forbes (2004), we keep only the firms that during the event window had more than 50% trading days of non-zero returns. Naturally, the database is limited to those publicly listed companies. After the process, we gathered stock data for 18,133 firms from 44 countries.

Cross-sectional and financial data is collected from several sources. The country of operation and the NAICS 4- and 6-digit codes are sourced from Refinitiv Eikon. All the yearly financial information is downloaded from the Worldscope database. As a measure of size, we compute the logarithm of net sales. We use the logarithm of the net sales to working capital ratio for productivity, because there is more availability of data for working capital than number of employees. As controls, following Greenland et al. (2020), we use market capitalization ($MktCap$), property, plant, and equipment (PPE), leverage (debt to equity ratio), profitability (cash flows to current assets ratio and EBITDA to net sales ratio), and overvaluation (Tobin's Q). The DiD equations use the growth in net sales, employees, intangible assets, and total capital as dependent variables, which are sourced for the years between 2011 and 2019.

Finally, to proxy for trade exposure, we base our analysis on the one by Forbes (2004) and create two variables: ImportsUS_i and ExportsChina_i. First, using the concordance table constructed by Pierce and Schott (2012), we relate the harmonized system (HS) 6-digit code with each NAICS 6-digit code. The HS codes represent the different goods sold by firms, and the NAICS codes represent the specific industries. Each NAICS 6-digit code may be related to more than one HS code. First, if the NAICS code of the company is related to at least one product (represented with the HS code) for which the US has more than the 25% of the total world imports, the variable ImportsUS_i takes the value of 1, and 0 otherwise. Accordingly, for firms with at least one product for which China has more than 25% of the world's total exports, the variable ExportsChina_i takes the value of 1, and 0 otherwise. These two measures attempt to capture the effects of the tariffs, which are focused on imports to the US and exports from China.

Some graphical analyses consider all the companies because they have their respective abnormal return and volatility. However, for the models' estimations, the number of observations may be reduced due to the availability of financial data.

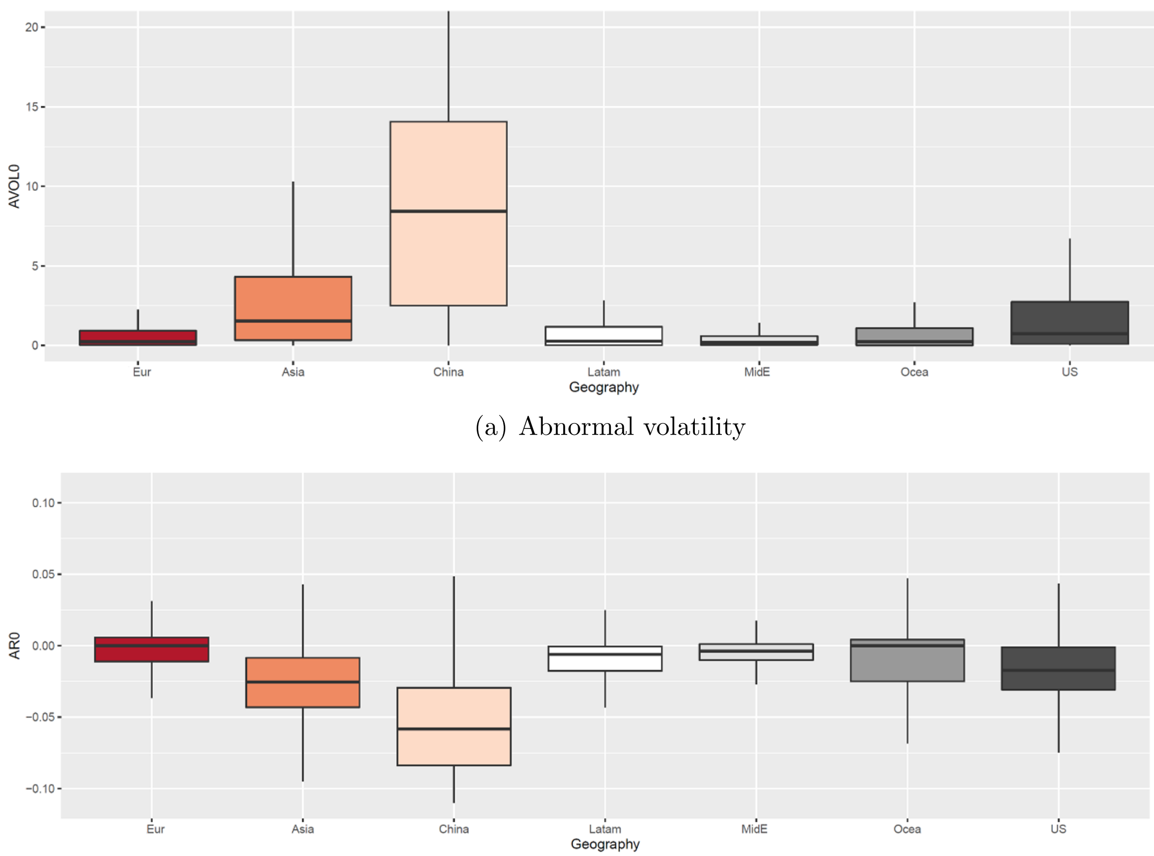
5 Results

5.1 Graphical results

Existing international trade theories at the micro-level define specific characteristics of how a change in tariffs affects expected earnings. According to this, it is crucial to explain that the analysis of volatility and returns should be done jointly. The reason is that volatility is a variable that takes only positive values and speaks about the magnitude of change in the stock return. Therefore, high volatility alone summarizes that portfolio managers anticipate a change in expected future earnings and its volatility. However, there is no way of knowing whether this is a positive or negative forecast. If we analyze return and volatility together, we have information on how much analysts overreacted to the trade announcements and the price change direction. Because of this, throughout the paper's results, we study jointly the results for abnormal volatility and abnormal returns.

The first graphical analysis is focused on geography. For this, we divide the sample by geographic zone. Specifically, we created subsamples to account for the five continents, separating China and the US. Figure 1 exhibits graphically the reaction in returns and volatilities for the firms separated by zones. Panel (a) shows that China, followed by Asia and the US, were the geographic zones where companies experienced the highest abnormal volatility during the event day. Likewise, these were the three zones where the most negative abnormal returns occurred compared to the rest of the world, as Panel (b) shows. The reason why Asian firms experienced this reaction may be explained by the fact that, after the US, the top trading partners for China are Hong Kong, Japan, South Korea, and Vietnam. Thus, as an indirect effect, firms in Asia also experienced high uncertainty. Egger and Zhu (2021) also finds that the trade war affected not only stock prices in China but also in the rest of the world.

Figure 1: AVOL and AR box plots by geography



(a) Abnormal volatility

(b) Abnormal returns

Notes: The figure reports the boxplots for the abnormal volatility in Panel (a) and for abnormal returns in Panel (b), as defined in equations (3) and (2). $AVOL_i$ uses a 10-day GARCH(1,1) forecast as the counterfactual in the denominator. The sample is separated by geographies.

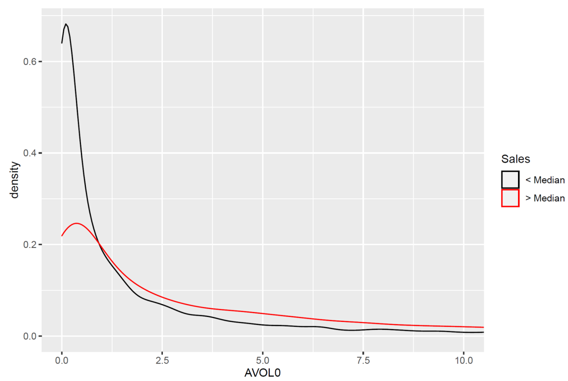
According to financial and trade characteristics, the first hypothesis that we want to test is regarding the size. Even though larger firms show to be the ones with higher productivity, they are those with more access to international trade and stock markets, for example, due to their higher liquidity and less incomplete information (Merton, 1987). Our sample covers stocks of publicly listed firms worldwide, and we do not filter for those who have access to international trade. Thus, given that the larger firms are those participating more in global markets and are those with higher liquidity in the stock markets, we study the size hypothesis following this specific reasoning that, naturally, larger firms are more vulnerable to international trade disputes. As we measure size with the net sales for each company, the first step is to split the sample in two according to the median of the sales. The process is made with data for 2017. Figure 2's Panels (a) and (b) show the densities for abnormal volatility and abnormal return. As suggested by Panel (a), companies with size above the median experienced higher abnormal volatility, which is explained by the heavier tail of the red line. In line with the above, Panel (b) shows that firms with sales above the median are more concentrated in the left tail of the density of abnormal returns, suggesting that larger firms were more negatively affected. These two plots give an initial intuition about the size hypothesis: larger firms suffer from a more considerable overreaction in terms of volatility and a more negative abnormal return, suggesting more exposure to the announcement by the US.

Productivity is also a crucial factor in international trade literature and heterogeneous firm models. According to the Melitz's (2003) model, firms with more advantage in international trade are those that show higher productivity. Thus, the connection with future earnings, and therefore the stock price via the dividend discount model, should show that the stocks of the most productive firms experience less negative abnormal returns than the less productive ones. The income effect better explains this than the substitution effect, which we will study later. Firms that are more productive, but are still affected by the announcement somehow, will also experience a reduction in expected future earnings. Still, models such as those of Breinlich (2014) and Melitz (2003), allow us to see that these are the ones that will adapt more quickly to the new challenges of international trade.

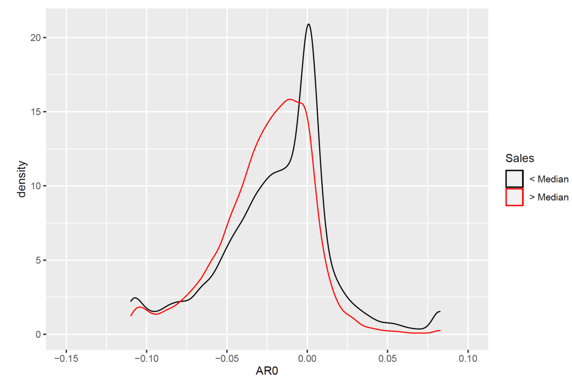
A graphical approach to test the hypothesis of productivity can be found in Panels (c) and (d) of Figure 2. In this case, we split the sample according to the median of the sales to working capital ratio and plot the density distribution for the abnormal volatility and the abnormal return. Panel (c) shows that firms below the median in productivity experience higher abnormal volatility, which can be seen with the kurtosis: the tails are heavier than those with productivity higher than the median. However, the difference in tails is not as big as when we divide the samples by size. Panel (d) shows the densities according to the abnormal return. Again, what is expected is to find more negative abnormal returns in the less productive firms. This result can be seen graphically because the distribution of firms with productivity below the median has the left tail heavier and the right tail less heavy than the density of firms with productivity above the median. These two panels give us an indication of compliance with the productivity hypothesis.

Finally, Figure 2's Panels (e) and (f) show a graphical approach for testing the hypothesis of trade exposure. The complete sample is divided into two groups: the firms with at least one product for which China has more than 25% of the world's total exports, i.e., $\text{ExportsChina}_i = 1$, and those that do not, i.e., $\text{ExportsChina}_i = 0$. We chose this variable for the graphical analysis because the trade policy we are analyzing directly affects Chinese exports. However, it also indirectly affects those of other countries that export the same product line to the United States. The graphs show that the abnormal volatility is higher in companies of this type, which have more trade exposure in this particular event. In addition,

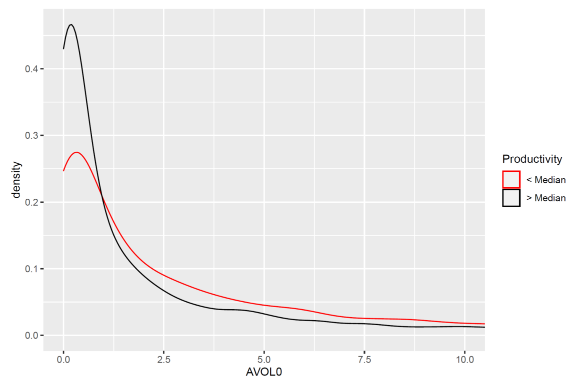
Figure 2: AVOL and AR densities by firm characteristics



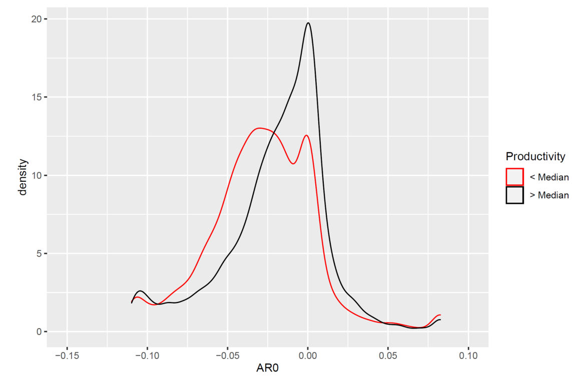
(a)



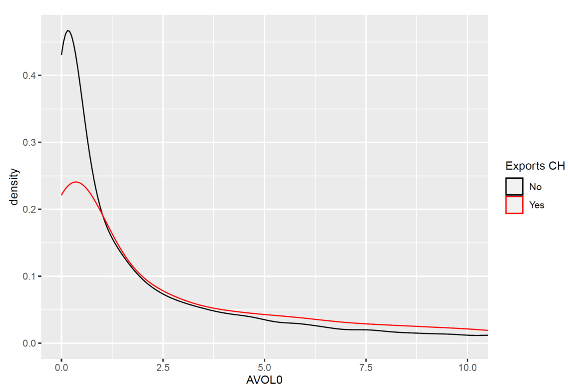
(b)



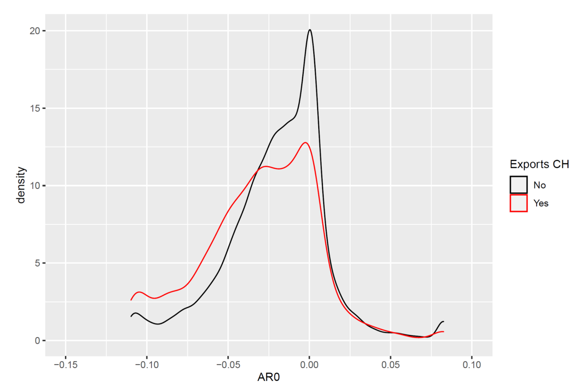
(c)



(d)



(e)



(f)

Notes: The figure reports the density distributions for the abnormal volatility (left-side panels) and for abnormal returns (right-side panels), as defined in equations (3) and (2). $AVOL_i$ uses a 10-day GARCH(1,1) forecast as the counterfactual in the denominator. The sample is separated by firm characteristics. Panels (a) and (b) split the sample by the median of the firm size. Panels (c) and (d) do it by the median of the firm productivity. Panels (e) and (f) divide the sample according to the variable ExportsChina$_i$.

the density of returns has a heavier tail to the downside for these types of firms worldwide.

In summary, the graphical results are in line with the expected hypotheses. In Section 5.2, we test these hypotheses formally with multivariate regressions.

5.2 Determinants of AVOL and AR

We are now focused on the estimations of equation (7), and (8). Table 1 and Table 2 show the results for the regressions for the complete sample and each geography, considering that the tariffs were focused on specific regions.[6]

Table 1: AVOL determinants using GARCH volatility

	Dependent variable: Abnormal volatility$_i$						
	All	Europe	China	Asia	LatAm	Oceania	US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size$_i$	-0.012	0.063	1.294***	0.517***	-0.002	0.252***	0.122
	(0.060)	(0.075)	(0.332)	(0.073)	(0.268)	(0.093)	(0.078)
Productivity$_i$	-0.226^{***}	-0.003	-0.605^{**}	-0.390^{***}	0.126	-0.250^{***}	0.013
	(0.027)	(0.067)	(0.276)	(0.052)	(0.108)	(0.078)	(0.066)
ImportsUS$_i$	-0.267	0.050	-0.039	-0.199	-0.501	-0.373^{*}	-0.270
	(0.233)	(0.163)	(0.579)	(0.318)	(0.402)	(0.218)	(0.224)
ExportsChina$_i$	0.494**	-0.108	0.595	0.406	-0.409	-0.114	0.357
	(0.242)	(0.172)	(0.574)	(0.316)	(0.427)	(0.274)	(0.217)
MktCap$_i$	0.665***	-0.003	-3.329^{***}	0.118**	0.806**	-0.088	0.303***
	(0.063)	(0.096)	(0.414)	(0.059)	(0.334)	(0.089)	(0.065)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,811	1,649	1,673	5,267	190	575	1,380
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6
Adjusted R^2	0.111	0.021	0.069	0.149	0.132	0.035	0.115

Notes: The table reports the estimations for the OLS equation (7) where the dependent variable is the abnormal volatility defined in equation (3) using a 10-day GARCH(1,1) forecast as the counterfactual in the denominator. The controls are MktCap, PPE, Leverage, and Cash. All the variables are defined in Table A.2, and the financial data is for 2017, the year previous to the announcement. Industry fixed effects are made at the NAICS 4-digit code. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 6-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The regressions test the hypotheses of size, productivity and trade exposure jointly. The measure for abnormal volatility in Table 1 is the one that uses the GARCH 10-day forecast as the counterfactual in the denominator of equation (3). All the regressions consider the

[6]Middle East is omitted because the number of firms is too low.

Table 2: AR determinants

	Dependent variable: Abnormal return$_i$						
	All	Europe	China	Asia	LatAm	Oceania	US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size$_i$	0.0001	−0.0001	−0.001	−0.002***	0.0001	0.001	0.001
	(0.0004)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Productivity$_i$	0.002***	−0.001*	0.0001	0.003***	−0.001	−0.001	0.001
	(0.0002)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)
ImportsUS$_i$	0.003	0.001	0.004	0.002	0.0004	−0.004	0.004*
	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.005)	(0.002)
ExportsChina$_i$	−0.006***	0.0004	−0.009**	−0.004	0.004	−0.007*	−0.009***
	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)
MktCap$_i$	−0.003***	−0.001	0.005**	−0.00001	−0.003**	−0.005**	−0.002**
	(0.0004)	(0.001)	(0.002)	(0.0005)	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,811	1,649	1,673	5,267	190	575	1,380
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6
Adjusted R^2	0.114	0.032	0.101	0.085	0.110	0.002	0.045

Notes: The table reports the estimations for the OLS equation (8) where the dependent variable is the abnormal return defined in equation (2). The controls are MktCap, PPE, Leverage, and Cash. All the variables are defined in Table A.2, and the financial data is for 2017, the year previous to the announcement. Industry fixed effects are made at the NAICS 4-digit code. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 6-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

winsorized control variables in 2017, the year before the announcement. Standard errors are clustered at the NAICS 6-digit code level. Finally, we control for industry fixed effects (NAICS 4-digit code) to avoid biases in our coefficients of interest due to industry trends.

Again, the analyses are made considering volatility and returns jointly. Columns (3), (4), and (6) of Table 1 show that size is significant at the 5% level for firms in China, Asia, and Oceania, giving evidence that larger firms experienced higher volatility during March 22, 2018. The results are consistent with the size hypothesis. In addition, there is a geographic effect, which speaks to tariff targeting. However, the size hypothesis on abnormal returns (Table 2) only holds in Asia. The results suggest that larger Asian firms have more access to international markets. In addition, the results also suggest that, in the case of China and the United States, other factors were more significant than size, such as trade exposure, which we will see below. Europe, Latin America, and Oceania do not show a significant effect, which is also reflected in Panel (b) of Figure 1, where the density of abnormal returns is close to 0, i.e., in general, these geographies do not seem to have been significantly affected by the announcement. Europe and part of Latin America were going to be exempted from the tariffs, explaining the lower stock reaction. Another explanation for the non-significance of the size factor is that we control for the industry effect, and since the tariffs were focused on specific sectors, it may be a more significant driver. In both tables, we show the control for MktCap_i. The coefficients of this control are generally positive for abnormal volatility and negative for abnormal returns when significant. The only exception is China. This result suggests that the size effect was driven mainly by access to stock markets in general, except for China. An explanation can be that firms with more market capitalization and thus more liquidity see future information reflected in their price more efficiently.

The results also show that the more productive firms are the ones that experienced lower volatility and higher abnormal return, in line with the hypothesis. Let us first focus on the abnormal returns in Table 2. According to our hypothesis, the direction of the coefficient in the AR regression suggests that the market is giving a signal that firms, the more productive they are, the more they will be able to take advantage of this trade war to increase their expected future earnings, specifically Asian firms. In line with this, the coefficient is positive and significant in Asia but statistically not different from 0 in China and other geographies, suggesting that, in the two leading players in the trade war, other factors such as trade exposure determine more the change in expected future earnings. Europe shows a negative relation, but again, as seen in Panel (b) of Figure 1, European firms do not show evidence of wide abnormal returns. Analyzing abnormal volatility, results for the entire sample, China, Asia, and Oceania, indicate that more productive firms experienced less abnormal volatility, suggesting investor confidence in the robustness of firms to the announcement and, therefore, in their earnings.

Finally, the third and fourth rows show the results for the trade exposure hypotheses. The variable ImportsUS_i represents firms in the same product line in which the US is the leading importer. Due to the increase in tariffs, what is expected is to see a substitution effect from the US, i.e., producers in the US may take advantage of the announcement to substitute suppliers in the US market. The market reacted in a corresponding manner, which explains the positive and significant coefficient for ImportsUS_i in Table 2 for the US and non-significant for the others. On the other hand, the fourth row shows a negative relationship between being exposed to the goods that China exports and abnormal returns. The significance is present for the entire sample, China, the US, and Oceania. The direction of the sign and significance can be explained by an income effect, suggesting that expected future earnings decreases after the imposition of the tariff schedule. Results provide information for portfolio management against future tariff policies to avoid experiencing lower returns by diversifying stocks between those competing with the leading exporter and the leading importer. Table 1 indicates that abnormal volatility was not mainly driven by trade exposure, as it is driven mainly by size and productivity.

Summarizing, the predictions of Breinlich (2014) are in general fulfilled. The estimations are robust to using the historical volatility as the counterfactual for the variance, as Table A.1 in the appendix shows. The results have several implications. For policymakers, it is crucial to consider that, in general, markets suffered drops in prices and higher risk after the tariff announcement. For managers, assuming that the tariffs may influence future earnings and cash flows, the estimations indicate that investors discount the future expected results in the current price. Therefore, the market identifies which firms will suffer the most due to the policy. However, to test formally if the market does a good job, in Section 5.3, we use both $AVOL_i$ and AR_i as explanatory variables for future financial outcomes.

5.3 Explaining firm outcomes with AVOL and AR

Once we have identified the heterogeneous firm responses to the announcement of March 22, 2018, we study if future expected financial results changes are appropriately reflected in current stock prices. This does not mean that changes in stock prices directly affect firm results, but if the market is doing a good job, abnormal returns and abnormal volatility may work as an indicator and as a tool to forecast future financial outcomes (Greenland et al., 2020).

The first variable that we study is sales growth. As specific firm characteristics drive stock reactions, Table 3 studies the results for equations (9) and (10) using the fixed effects within estimator and separating the sample by geography. All the regressions consider the winsorized control variables for 2017. The first two columns use the entire sample to estimate the regressions. The results indicate a direct relationship between abnormal returns experienced on March 22, 2018 and the sales growth in the following years. The results are consistent with the theories, hypotheses, and our previous results. As we see in the other columns, the results are driven by the Chinese firms, which also show that firms with more negative abnormal returns generally suffer declines in future sales. Moreover, the sign and significance of abnormal volatility are the expected for China: a direct relationship between having experienced high abnormal volatility and a reduction in future sales. However, for the rest of the geographies, the results are non-significant, suggesting that in the middle term, the market identified that the first announcement was going to affect mainly Chinese firms.

This same analysis is performed by separating the entire sample by firm characteristics. Table 4 shows the results for equations (9) and (10) for firms with sizes larger than the median vs. those with sizes lower than the median; for firms with productivity higher than the median vs. those with lower productivity; and for companies with higher trade exposure ($\text{ExportsChina}_i = 1$) vs. those with lower trade exposure ($\text{ExportsChina}_i = 0$). Results show that the market did a good job with the stock price reaction of larger, more productive, and more exposed firms. It makes sense because more productive firms are usually larger and with more participation in international markets (Breinlich, 2014) and larger firms have also more liquidity in stock markets (Merton, 1987). The results suggest that if an investor is trying to calculate the present value of a firm with these characteristics, she can use the abnormal return and abnormal volatility to forecast the sales growth in the model.

We also care about the direction of the coefficients. In all the cases mentioned, lower abnormal returns are related to lower sales growth, i.e., there is a direct relationship. Greenland et al. (2020) also find this positive relationship between sales and abnormal returns for US

Table 3: AVOL, AR and Sales by geography

	Dependent variable: $\Delta \log(Sales)_{it}$									
	All		China		Asia		Oceania		US	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post \times AVOL_i$	-0.000620		-0.00200*		0.00121		0.00668		0.00203	
	(0.000486)		(0.00111)		(0.000746)		(0.00761)		(0.00175)	
$Post \times AR_i$		0.218**		0.480**		-0.125		-1.129		0.171
		(0.0854)		(0.211)		(0.127)		(0.883)		(0.268)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74684	74684	12806	12806	38112	38112	1952	1952	7923	7923
Firms	12025	12025	1980	1980	6067	6067	379	379	1328	1328
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.031	0.031	0.029	0.029	0.031	0.031	0.049	0.050	0.032	0.032

Notes: The table reports the estimations for the OLS DiD panel equations (9) and (10) for $\Delta \log(Sales)_{it}$, where Post is a dummy variable for the years post-event (2018 and 2019) interacting with the covariates. $AVOL_i$ and AR_i are defined in equations (3) and (2). The controls are MktCap, PPE, Leverage, Cash, and EBITDA. The estimations are for yearly data between 2012 and 2019. All the variables are defined in Table A.2, and the controls are for 2017, the year previous to the announcement. Firm and year fixed effects are used. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

firms. On the other hand, higher abnormal volatility is related to lower sales growth in the following years. The table results illustrate how asset prices can be a good measure of trade exposure to tariff announcements in the US-China trade war.

Table 5 analyzes the results for the equations (9) and (10) for the number of employees. Column (1) shows a similar relationship between stock reactions and the growth of employees to the one we found with sales growth. That means that the more negative abnormal return and higher abnormal volatility, the more companies experience a future drop in the number of employees. The market anticipates a decline in firms' operations, including production decisions. If we assume that production and sales are dependent on capital and employment, the transmission mechanism can be investigated, which is out of the scope of this research. However, studying the relationship between market reactions and hiring decisions could provide a tool for policymakers focused on lowering unemployment since the result suggests that a restrictive trade policy could affect the firms that show worse stock reactions in the long run. Moreover, when we split the sample by firm characteristics, we find that larger and more productive firms show better explanatory power for stock market reactions. On the other hand, there is no difference in sign and significance between those more and less exposed to this trade policy.

Capital decisions are directly affected by trade liberalization decisions, i.e., by obtaining more competition, firms innovate more via capital increase (Gutiérrez & Philippon, 2017). Tables 6 and 7 show that the more volatility the firm experienced, the more uncertainty it created in future expected outcomes, which translated into lower capital investment. On the returns side, the market predicted a direct effect, as we found a positive and significant relationship between abnormal returns and future capital growth. The result suggests a

Table 4: AVOL, AR and Sales by firm characteristics

Panel A: Abnormal volatility

	Dependent variable: $\Delta \log(Sales)_{it}$					
	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times AVOL_i$	-0.00111*	0.00107	-0.00204***	0.000765	-0.000695	-0.000601
	(0.000634)	(0.000807)	(0.000547)	(0.000700)	(0.000270)	(0.000646)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46964	27720	45161	29523	21285	53399
Firms	6770	5255	7186	4839	3374	8651
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.041	0.023	0.040	0.028	0.034	0.031

Panel B: Abnormal returns

	Dependent variable: $\Delta \log(Sales)_{it}$					
	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times AR_i$	0.552***	-0.266	0.471***	-0.0316	0.227**	0.224
	(0.136)	(0.217)	(0.105)	(0.274)	(0.0311)	(0.146)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46964	27720	45161	29523	21285	53399
Firms	6770	5255	7186	4839	3374	8651
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.042	0.024	0.040	0.028	0.034	0.032

Notes: The table reports the estimations for the OLS DiD panel equations (9) and (10) for $\Delta \log(Sales)_{it}$, where Post is a dummy variable for the years post-event (2018 and 2019) interacting with the covariates. $AVOL_i$ and AR_i are defined in equations (3) and (2). The controls are MktCap, PPE, Leverage, Cash, and EBITDA. The estimations are for yearly data between 2012 and 2019. All the variables are defined in Table A.2, and the controls are for 2017, the year previous to the announcement. Firm and year fixed effects are used. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 4-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

link between earnings and capital, where the possible transmission mechanism is due to an income effect (reduction in market share for targeted firms) or a reduction in competition, which shortens the incentives to invest in new capital to innovate (Gutiérrez & Philippon, 2017). Greenland et al. (2020) also find a direct relationship between abnormal returns and future capital and employment after a trade policy in the US. As the results between Tables 6 and 7 are comparable in magnitude, we can mention that the relationship of both abnormal return and abnormal volatility on the growth of intangibles is almost twice that of total capital. This result suggests that the impact on capital is via decreases in developments such as patents rather than physical capital. Again, the indicators show a higher predictive power for larger and more productive firms.

The information contained in the table suggests that using stock market reactions as a metric of policy exposure could have predictive power not only on sales but on other financial variables that represent business decisions to adapt to the new economic environment.

Table 5: AVOL, AR and Employees by firm characteristics

Panel A: Abnormal volatility

	Dependent variable: $\Delta \log(Employees)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AVOL_i$	-0.00169**	-0.00188***	-0.00159	-0.00204***	0.000765	-0.00115***	-0.00188**
	(0.000621)	(0.000592)	(0.00143)	(0.000547)	(0.000700)	(0.0000414)	(0.000804)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54692	40098	14594	45161	29523	14886	39806
Firms	10112	6410	3702	7186	4839	2816	7296
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.030	0.029	0.035	0.040	0.028	0.027	0.031

Panel B: Abnormal returns

	Dependent variable: $\Delta \log(Employees)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AR_i$	0.574**	0.741***	0.155	0.471***	-0.0316	0.299***	0.708***
	(0.203)	(0.205)	(0.335)	(0.105)	(0.274)	(0.0196)	(0.214)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54692	40098	14594	45161	29523	14886	39806
Firms	10112	6410	3702	7186	4839	2816	7296
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.030	0.030	0.035	0.040	0.028	0.027	0.032

Notes: The table reports the estimations for the OLS DiD panel equations (9) and (10) for the growth in the number of employees ($\Delta \log(Employees)_{it}$), where Post is a dummy variable for the years post-event (2018 and 2019) interacting with the covariates. $AVOL_i$ and AR_i are defined in equations (3) and (2). The controls are MktCap, PPE, Leverage, Cash, and EBITDA. The estimations are for yearly data between 2012 and 2019. All the variables are defined in Table A.2, and the controls are for 2017, the year previous to the announcement. Firm and year fixed effects are used. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 4-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusions

This thesis presents a new approach to international finance studies. Using abnormal volatility and abnormal returns, we show the worldwide heterogeneous stock reactions to the tariffs announcement of the US against China on March 22, 2018. Stocks in China, the US, and Asia were the most negatively affected (negative returns and higher volatility). We find that firm size and trade exposure are related to lower returns and higher volatility on the announcement day. Trade exposure shows differences according to income or substitution effects. We also find that the market saw the more productive firms as the most resilient, as they experienced higher returns and lower volatility. The results give evidence of the heterogeneous effects of trade policies when there is a tariff increase.

Furthermore, we investigate if the abnormal returns and abnormal volatility work as a mea-

Table 6: AVOL, AR and Intangibles by firm characteristics

Panel A: Abnormal volatility

	Dependent variable: $\Delta \log(Intangibles)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AVOL_i$	-0.00382***	-0.00359**	-0.00384**	-0.00356**	-0.00408***	-0.00483***	-0.00322**
	(0.000667)	(0.00133)	(0.00148)	(0.00153)	(0.00124)	(0.000346)	(0.00136)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67966	44537	23429	40942	27024	19417	48549
Firms	11176	6530	4646	6638	4538	3154	8022
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.006	0.007	0.006	0.008	0.005	0.005	0.007

Panel B: Abnormal returns

	Dependent variable: $\Delta \log(Intangibles)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AR_i$	0.947**	1.261***	0.225	0.900*	0.950***	0.984**	0.933*
	(0.333)	(0.321)	(0.611)	(0.473)	(0.254)	(0.110)	(0.522)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67966	44537	23429	40942	27024	19417	48549
Firms	11176	6530	4646	6638	4538	3154	8022
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.006	0.008	0.006	0.008	0.005	0.006	0.007

Notes: The table reports the estimations for the OLS DiD panel equations (9) and (10) for $\Delta \log(Intangibles)_{it}$, where Post is a dummy variable for the years post-event (2018 and 2019) interacting with the covariates. $AVOL_i$ and AR_i are defined in equations (3) and (2). The controls are MktCap, PPE, Leverage, Cash, and EBITDA. The estimations are for yearly data between 2012 and 2019. All the variables are defined in Table A.2, and the controls are for 2017, the year previous to the announcement. Firm and year fixed effects are used. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 4-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sure of exposure to the policy, and we test if they work as an indicator and predictor for future financial outcomes. It means that financial markets are gathering information properly. As a result, we use a DiD panel fixed effects model, which employs an indicator variable for years after the event and it uses abnormal volatility and abnormal returns as explanatory variables. We select as dependent variables different financial outcomes linked to the possible effects of tariff imposition: sales, employees, intangibles assets, and capital. In particular, abnormal returns have a direct effect on these variables, and the effect of abnormal volatility over them is inverse. China is the region where those indicators have more explanatory power. Moreover, when we split the samples by firm characteristics, the effects are mainly present in larger, more productive firms and those more exposed to trade. Using these reactions as indicators to improve financial forecasts or evaluate policies can benefit managers, investors, and policymakers.

Overall, using abnormal stock market reactions is an adequate tool to investigate the heterogeneous impacts of trade policies on firms' outcomes and thus to know more about their effectiveness over the general level of the economy. For example, the evidence of a decrease

Table 7: AVOL, AR and Total Capital by firm characteristics

Panel A: Abnormal volatility

	Dependent variable: $\Delta \log(Capital)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AVOL_i$	-0.00217***	-0.00255***	-0.000242	-0.00369***	0.000222	-0.00200**	-0.00222***
	(0.000359)	(0.000400)	(0.00106)	(0.000460)	(0.00121)	(0.000336)	(0.000486)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74578	46937	27641	45061	29517	21262	53316
Firms	12024	6771	5253	7181	4843	3374	8650
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.021	0.021	0.024	0.025	0.027	0.020	0.022

Panel B: Abnormal returns

	Dependent variable: $\Delta \log(Capital)_{it}$						
	All	Size > Median	Size < Median	Prod > Median	Prod < Median	Exports China	Non-Exports China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post \times AR_i$	0.482***	0.753***	-0.0757	0.727***	-0.0136	0.303**	0.580***
	(0.104)	(0.162)	(0.111)	(0.174)	(0.179)	(0.0311)	(0.134)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74578	46937	27641	45061	29517	21262	53316
Firms	12024	6771	5253	7181	4843	3374	8650
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4	NAICS4
Adjusted R^2	0.021	0.022	0.024	0.025	0.027	0.020	0.022

Notes: The table reports the estimations for the OLS DiD panel equations (9) and (10) for the growth in total capital ($\Delta \log(Capital)_{it}$), where Post is a dummy variable for the years post-event (2018 and 2019) interacting with the covariates. $AVOL_i$ and AR_i are defined in equations (3) and (2). The controls are MktCap, PPE, Leverage, Cash, and EBITDA. The estimations are for yearly data between 2012 and 2019. All the variables are defined in Table A.2, and the controls are for 2017, the year previous to the announcement. Firm and year fixed effects are used. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 4-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in sales, employment, and capital growth in firms that experienced lower abnormal returns and higher abnormal volatility seems to support the benefits of trade liberalization over tariff impositions.

As a limitation of the study, estimating both returns and volatilities for each firm individually omits the possible effect of other systematic risks. A possible solution to this is to make a sensitivity analysis. Future research may be focused on calculating the abnormal volatility using other measures of volatility that may take more elements of market microstructure and systematic risks, such as the ones proposed by Yang and Zhang (2000). Finally, the results are focused on the event of March 22, 2018, when the first tariff measures focused on China were debated in the US. However, the trade war has had several episodes after this one. Future research also needs to handle this issue to give more robust results using information from different events and tariff announcements.

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Appendix

Table A.1: AVOL determinants using historical volatility

	Dependent variable: Abnormal volatility$_i$						
	All	Europe	China	Asia	LatAm	Oceania	US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size$_i$	-0.107	0.001	0.810*	0.489***	0.098	0.207***	0.132
	(0.069)	(0.072)	(0.415)	(0.084)	(0.132)	(0.069)	(0.083)
Productivity$_i$	-0.253^{***}	-0.004	-0.160	-0.478^{***}	0.069	-0.189^{***}	0.017
	(0.033)	(0.057)	(0.329)	(0.067)	(0.069)	(0.062)	(0.072)
ImportsUS$_i$	-0.150	0.174	-0.150	0.131	-0.323	-0.328^{*}	-0.299
	(0.266)	(0.190)	(0.662)	(0.370)	(0.301)	(0.172)	(0.221)
ExportsChina$_i$	0.628**	-0.233	1.050	0.363	-0.228	-0.201	0.243
	(0.267)	(0.196)	(0.670)	(0.318)	(0.279)	(0.229)	(0.223)
MktCap$_i$	0.787***	-0.052	-1.782^{***}	-0.025	0.368**	-0.030	0.417***
	(0.077)	(0.083)	(0.517)	(0.068)	(0.161)	(0.067)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,322	1,766	1,868	5,357	201	630	1,421
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6	NAICS6
Adjusted R^2	0.096	0.025	0.038	0.113	0.094	0.032	0.158

Notes: The table reports the estimations for the OLS equation (7) where the dependent variable is the abnormal volatility defined in equation (3) using the historical historical daily volatility during all 2017 as the counterfactual. The controls are MktCap, PPE, Leverage, and Cash. All the variables are defined as in Table A.2 and the financial data is for 2017, the year previous to the announcement. Industry fixed effects are made at the NAICS 4-digit code. All financial covariates were winsorized at the 1 percent level. Standard errors are presented in parenthesis, clustered by the NAICS 6-digit code. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Variables description

Variable	Description
Size	Logarithm of the net sales. In USD.
Productivity	Logarithm of the net sales to working capital ratio. In USD.
ImportsUS	1 if the firm is in the same product line (HS code) to those where the US has more than the 25% of the world total imports, 0 otherwise. Based on Forbes (2004) and made by using the concordance table by Pierce and Schott (2012).
ExportsChina	1 if the firm is in the same product line (HS code) to those where China has more than the 25% of the world total exports, 0 otherwise. Based on Forbes (2004) and made by using the concordance table by Pierce and Schott (2012).
MktCap	Logarithm of the total market capitalization. In USD.
PPE	Logarithm of property, plant, and equipment. In USD.
Leverage	Logarithm of the debt to equity ratio.
Cash	Logarithm of the cash flow to current assets ratio.
EBITDA	Logarithm of the EBITDA to net sales ratio.
Tobin's Q	Market capitalization divided by firm's book value.