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Firm-Level Exposure to Trade Policy Shocks: A Multi-dimensional Measurement Approach

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Executive Summary

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Trade policy influences the financial performance of firms. Moreover, shifts in trade policy will have heterogeneous effects across such businesses; some may benefit from a more globalised market via reduced input costs or more export opportunities, while others may benefit from the introduction of protectionist policies via a reduction in foreign competition. A measure that captures the impact of shifts in trade policy on firms is therefore a useful tool for researchers in finance or economics and financial market participants alike.

We propose such a firm-level measure of exposure to trade policy shifts. The measure draws on data regarding the tradability of produced goods, the share of output exported, and corporate risk disclosures. Furthermore, it also incorporates information from stock returns. This multi-dimensional measure has the advantage that it uses a broad set of information. International trade is complex, so we cannot expect a single data source to capture exposure to shifts in trade policy accurately. Combining multiple metrics also reduces the impact of noise present in each of them individually.

We show that the measure reliably captures out-of-sample differences in exposure to trade policy shifts across firms. First, we find that firms with a high exposure according to our measure have a more negative stock price reaction around tariff announcements than firms with a low exposure. This result is both statistically and economically significant, with a 140bp difference during the week following the announcement, as shown in Exhibit 1. Second, in times of rising trade tensions, high exposure firms discuss trade policy with a more negative sentiment than low exposure firms in their quarterly earnings calls. Supportive out-of-sample evidence based on two entirely different data sources strengthens our confidence in the validity of the measure. Moreover, we show that standard firm classifications by size and industry are insufficient to capture such heterogeneity in trade policy exposures and we present evidence both in US and international data.

Exhibit 1: Stock price reaction to tariff announcements
The table reports the stock price reaction during the week following tariff announcements for high and low trade policy exposure firms. T-statistics are indicated between brackets. See Exhibit 5 in the paper for more details on the applied methodology.

Stock price reaction to tariff announcements	Tradability	Export share	Risk disclosures	Combined
High exposure stocks	-0.4%	-0.4%	-0.6%	-0.7%
	(-1.3)	(-1.5)	(-2.4)	(-2.8)
Low exposure stocks	0.3%	0.7%	0.7%	0.7%
	(1.1)	(2.1)	(2.2)	(2.1)

While the focus of this paper is on the measure of exposure to trade policy shifts and its validation, we also discuss a variety of potential applications. The firm-level granularity and reliance on ex-ante available data makes the measure suitable for a wide range of applications. Among others, we expect the measure to be useful for researchers interested in the economic effects of international trade policy or asset pricing, or for investors who want to manage the trade policy risk exposure in their equity portfolio.

1. Introduction

1. Introduction

Trade policy influences the financial performance of firms. It affects the cost and availability of foreign inputs, access to export markets, and the extent of foreign competition. Shifts in trade policy will have heterogeneous effects across firms (e.g., Fajgelbaum et al., 2020). For example, more productive firms tend to thrive with trade liberalisation while less productive firms benefit from protectionism (Melitz, 2003, Bernard, Jensen, and Schott, 2006).

This paper analyses a firm-level measure of exposure to shifts in trade policy and documents it captures substantial heterogeneity across firms in their reaction to trade policy shifts. This measure combines multiple dimensions of trade policy exposure and exploits information in stock return covariance in addition to industry and firm characteristics. We show in detailed validation tests that the measure captures heterogeneous exposure of firms to trade policy shocks in terms of both stock price reactions and sentiment on trade policy. Importantly, the measure is available ex ante at the firm level and effectively captures heterogeneous responses ex post. We also show that the measure is not subsumed by information contained in standard firm classifications into size categories or industries.

Such a measure can be used in several academic and practical applications. For example, the impact of changes in trade policy needs to be well understood by policy makers. The exposure measure allows to identify which areas of the economy will benefit or suffer from proposed changes. Furthermore, accurate measurement of exposure to shifts in trade policy is needed in asset pricing research to test whether this is a priced risk. It also allows to construct investment portfolios that enable investors to manage trade policy risk, be it to harvest a potential premium or to hedge undesired exposures in non-tradable components of their wealth.

Previous research has used several measures to capture firms' exposures to shifts in trade policy. Barrot, Loualiche, and Sauvagnat (2019) use shipping costs for a firm's goods, following Bernard, Jensen, and Schott (2006), to measure exposure to globalisation. High shipping costs are structural economic barriers that decrease the potential for international trade. This low tradability will make it less likely for a firm to sell its goods internationally. Therefore, firms producing products with high shipping costs, or low tradability, are less exposed to international trade flows and the risk of shifts in trade policy. Furthermore, Tian (2018) distinguishes between firms based on the proportion of their output that is exported. Firms which export a larger fraction of their output are more exposed to changes in international trade policy. Yet another approach to capture exposure to shifts in trade policy is to use textual analysis of a firm's risk disclosures (see Baker, Bloom, and Davis, 2016, and Caldara et al., 2020). A firm's management could indicate themselves that the firm is exposed to the risk of the introduction or removal of trade barriers.

We propose a multi-dimensional measure of exposure to shifts in trade policy by combining these three individual measures[1]. Furthermore, we also include information about stock return covariances. Stock returns allow to capture relevant firm-level information based on the assessment of market participants. Stocks with a high exposure according to this measure are expected to

1 - We note that it could be desirable for some applications to omit certain components of our measure. For example, textual analysis that identifies stocks exposed to trade policy risk will lead to false positives that can be easily identified by human analysts. Even if such a measure adds information on average, occurrence of false positives might not be acceptable for investors who conduct an analysis of their portfolio holdings. This could motivate removing the textual analysis component in investment applications.

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perform well when trade barriers decrease, so we call them trade peace stocks. Similarly, stocks with a low exposure are expected to perform relatively well when trade barriers increase and are called trade war stocks.

Compared to the measures proposed previously, our multi-dimensional measure has the advantage that it uses a broader set of information. International trade impacts firms via different, interdependent channels (Bernard et al., 2018). Given this complexity, we cannot expect that a single source of information captures exposure to shifts in trade policy accurately. Furthermore, combining multiple measures reduces the impact of noise present in each of them individually (see Kahneman, Sibony, and Sunstein, 2021). Therefore, we expect that a multi-dimensional measure captures exposure to trade policy risk more accurately. This paper provides empirical evidence supporting this idea. A related advantage of combining several measures is that results of empirical analysis will not be overly dependent on variable selection choices.

To ensure that proxies of trade policy exposure effectively capture the economic risks they target, we conduct tests that assess heterogeneous effects of trade policy shocks across firms. When using a reliable measure of exposure to group firms by their expected sensitivity to trade policy shocks, high exposure firms should be significantly more negatively impacted than low exposure firms by out of sample shocks. Such cross-sectional validation of exposure measures is an important step before analysing further economic differences across high and low exposure firms. We follow a double validation procedure, assessing heterogeneity of firm-level effects of trade policy events in terms of both stock price reactions and sentiment on trade policy.

We analyse the effect of trade policy events on stock prices via the abnormal return around tariff announcements between the US and China, following Amiti, Kong, and Weinstein (2020). Abnormal returns can be interpreted as an ex-post measure of exposure to trade policy shifts[2], and are commonly used in the literature on international trade (e.g., Greenland et al., 2020; Fisman, Hamao, and Wang, 2014; Davies and Studnicka, 2018)[3]. We show that our multi-dimensional exposure measure (which is based on data known before the events) significantly explains cross sectional variation in the abnormal returns observed around these events. Moreover, each of the individual dimensions has incremental explanatory power over the other two in these tests. At the same time, none of them add value when controlling for the combined measure. This indicates that a combination of these measures is useful to capture exposure to trade policy shifts.

These tests allow us to document statistically significant heterogeneity across firms. Trade peace stocks have on average a negative cumulative abnormal return of around 70bp from the day of the tariff announcement until one week after. Trade war stocks, on the other hand, have a positive cumulative abnormal return of around 70bp in the same time window. Apart from their statistical significance, these results are also large in terms of economic magnitude. Indeed, the 140bp difference in abnormal returns between trade peace and trade war stocks represents more than 10 times the average weekly excess return of the US equity market, which is 12bp, and almost two

2 - Compared to using the abnormal returns directly as an exposure measure, as in Greenland et al. (2020), our measure is available ex ante. Furthermore, abnormal returns are a noisy and purely empirical measure, whereas our exposure measure is based on fundamental economic mechanisms.
3 - Abnormal returns are also used to study the impact on the equity market of other events, such as disasters. See for instance Ding et al. (2021) and Pagano, Wagner, and Zechner (2022), who study the impact of the recent pandemic outbreak.

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thirds of the 222bp weekly standard deviation of market returns[4]. The average cumulative abnormal returns are also large relative to the impact on stock returns of other important events, such as the pre-announcement effect of Federal Open Market Committee (FOMC) meetings[5].

To assess heterogeneity of firm-level sentiment on trade policy, we analyse text in quarterly earnings calls[6]. We identify text that discusses trade policy topics and measure its sentiment, following the methodology of Hassan et al. (2019). Earnings calls include a presentation by the firm's management and a Q&A session with external analysts. The measured sentiment therefore captures both internal and external perspectives on the impact of trade policy on the firm. In cross-sectional regressions, we find that trade peace firms tend to have a significantly more negative trade sentiment than trade war firms in times of rising trade tensions. In the cross section, a one standard deviation increase in exposure corresponds to a decrease in sentiment of one tenth of a standard deviation. To put this number into perspective, this decrease in sentiment is more than half the drop in average trade sentiment observed during the 2018 spike in trade tensions.

Overall, this double validation procedure provides support that the proposed measure captures trade policy exposure. The results also document substantial heterogeneity of effects across firms. These results hold both in US and international data. In addition, we show that standard firm classifications by size and industry are insufficient to capture such heterogeneity. While the focus of this paper is on the multi-dimensional measure of exposure to trade policy shocks and its validation, we also discuss a variety of potential applications that could be explored in future research.

This paper is related to the literature on international trade, and more specifically to research that considers heterogeneity among firms. Melitz (2003) and Bernard et al. (2003) propose models that use differences in productivity to explain why some firms export while others don't. They show that a reduction in trade barriers benefits larger, more efficient firms, who tend to be exporters, while hurting the smaller, least efficient ones, who only serve the domestic market. Chaney (2008) expands these models by considering multiple countries with asymmetric trade barriers. Eaton, Kortum, and Kramarz (2004, 2011) also consider multiple export markets. Again, they show that lower trade barriers benefit large exporters while the corresponding import competition results in the exit of small, domestic firms. Instead of focusing on exports, Antràs, Fort, and Tintelnot (2017) analyse firms' sourcing decisions. As was the case for exports, there exists much heterogeneity across firms. Larger, more efficient firms are more inclined to import inputs. They point out that import decisions are more complex and interdependent than export decisions, due to their impact on marginal costs. Bernard et al. (2018) propose a framework in which export and sourcing decisions are combined. They also include other considerations, such as the choice between exporting and producing in foreign countries via foreign direct investment (Helpman, Melitz, and Yeaple, 2004), to model the environment of large global firms in more detail. This literature highlights the heterogeneity in the impact that firms experience from changes in trade barriers. We contribute by focussing on a practical measure to capture this heterogeneity and show that it subsumes the information contained in firm size, which is identified by these theories as being related to international trade exposure.

4 - We estimate the average and standard deviation of weekly excess equity market returns in the U.S. using the data from the Kenneth French Data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) over the period from the 1st of July 1963 to the 30th of June 2020.
5 - For instance, Lucca and Moench (2014) find that in the hours preceding the FOMC announcements, on average the S&P 500 experience an abnormal return of 0.5%.
6 - We discuss below that analyst earnings calls contain useful data to measure sentiment ex post but not to measure exposure ex ante (see section 5).

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To construct our measure of trade policy risk exposure, we draw on a literature that relates international trade exposure to properties of stock returns. For example, Tian (2018) finds that firms with a high proportion of output that is exported have more cyclical asset returns. Hoberg and Moon (2019) find that firms selling output abroad tend to have higher stock returns while firms purchasing input abroad have lower stock returns. This is consistent with the idea that offshore output is a source of risk, while offshore input can be used as a hedge. Barrot, Loualiche, and Sauvagnat (2019) measure exposure to international trade via shipping costs and find that exposed firms earn a risk premium. They point to the risk of increased import competition to explain the results. We also draw on methods of text analysis to capture exposure to trade policy risk. We exploit information in 10-K filings to construct our ex-ante exposure measure, and sentiment extracted from earnings call transcripts for ex-post validation (e.g., Hassan et al., 2019)[7]. We build on this literature and combine information from existing measures of trade policy exposure, as well as from stock return covariance.

This paper provides three contributions to the literature. First, we propose a multi-dimensional measure of exposure to shifts in trade policy. The measure combines previously proposed metrics, while adding information from stock return covariances. We argue that, due to the complex nature of international trade, including multiple dimensions helps to accurately capture exposures. Importantly, the measure is ex ante available at the firm level, which makes it suitable for a wide range of applications. Second, we conduct validation tests that focus on the cross-sectional variation of exposure to shifts in trade policy. Our double validation procedure makes use of ex-post reactions to trade policy shocks both in stock prices and in trade sentiment. The use of sentiment from text data is a valuable addition compared to previous work and allows testing whether the results based on stock returns are supported by an independent data source. Third, armed with a comprehensive measure of risk exposure and a framework for assessing reactions to trade policy events, we document significant heterogeneity in firms' reactions to tariff announcements related to the US-China trade war and global trade events. Again, we document this heterogeneity both in terms of stock returns and trade sentiment.

The remainder of this paper proceeds as follows. Section 2 describes how the trade policy exposure measure is constructed. Section 3 assesses firm-level heterogeneity in terms of stock price reactions. Section 4 tests for redundancy with standard firm classifications. Section 5 documents heterogeneity of trade policy sentiment. Section 6 contains the results based on international data. Finally, section 7 gives examples of potential applications where our measure can add value before section 8 concludes.

7 - Other relevant work in this area includes Baker, Bloom, and Davis (2016), who construct a measure of economic policy uncertainty, and Caldara et al. (2020), who focus on trade policy uncertainty specifically. Below, we argue that earnings call transcripts contain useful data for ex post validation but not necessarily for ex ante measurement, due to strong time variation in attention to trade policy in discussions between analysts and management.

2. Measuring Exposure to Shifts in Trade Policy

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This section outlines the construction details of our firm-level measure of exposure to shifts in trade policy. We draw on firm characteristics proposed in the literature: tradability, export share, and trade risk disclosures. These characteristics should capture the economic drivers of firms' sensitivity to shifts in trade policy. To alleviate issues in granularity and coverage that each of these metrics face, we augment firm characteristics with covariances of stock returns with the respective mimicking portfolio. This approach allows using information contained in stock returns to enrich the information that would be available from characteristics alone. To account for the multidimensional nature of trade policy exposure, we then combine those three dimensions. Our main analysis is based on a US stock universe consisting of the 1,000 largest firms traded on the New York Stock Exchange or Nasdaq. The universe is reconstituted quarterly on the third Friday of March, June, September, and December[8]. When referring to quarters in this paper, these are understood to start and end on these days. This universe of large and liquid stocks ensures results are relevant for investment applications.

Tradability

We obtain the annual data to construct our estimate of shipping costs from the US Census Bureau. Similar to Barrot, Loualiche, and Sauvagnat (2019), we define industry-level shipping costs based on the cost, insurance, and freight (CIF) import value and customs import value data fields, as follows.

$$Shipping\ costs = \frac{CIF\ Import\ Value}{Customs\ Import\ value} - 1$$

Shipping costs therefore captures the cost of insurance and freight to transport goods internationally, as a percentage of the value of the goods.

This data is classified into industries based on the North American Industry Classification System (NAICS). If available, we assign a value to industries at the most granular six-digit level industries. If the required data is not available at this level, we use the value for the corresponding four-digit level industry group, or the three-digit level subsector for the industry. If data are unavailable at this level, we consider the value missing. Every June, a stock is assigned the shipping cost value of its corresponding industry[9] based on data of the previous year. Note that shipping costs capture the opposite notion of tradability, high shipping costs means that a firm has low tradability. Consequently, when considering tradability, we rank stocks according to the negative of the shipping costs value.

A firm's tradability is based on the goods it produces. Therefore, the two key channels via which it captures exposure to shifts in trade policy are the possibility to sell the good abroad and competition from foreign firms selling similar goods. It does not necessarily capture the extent to which inputs can be sourced from abroad. Since we focus on a universe of relatively large stocks, we expect that the former effect dominates (e.g., Bernard et al., 2003). Larger firms benefit from the export possibilities while smaller firms run more risk of being displaced by import competition. Therefore, an increase in trade barriers will tend to have a negative impact on firms due to reduced export possibilities in our universe. Tradability captures the potential for international trade in a

8 - More specifically, we use data for the Scientific Beta extended US universe. The detailed construction process for this universe can be found in documentation accessible via www.scientificbeta.com.

9 - Note that the universe data for the Scientific Beta extended US universe available to us contains NACE industry classification codes. Therefore, we first map the NAICS 6-digit level industries to NACE codes, via publicly available industry mappings from ISIC to NAICS and ISIC to NACE.

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certain industry. Firms producing goods which are easily tradable will operate in a more global environment, since shipping costs present a form of trade barriers. These firms are therefore more exposed to the effects of shifts in trade policy. Consequently, if the government enacts a policy that results in increased trade barriers, tradable firms will suffer relatively more than non-tradable firms because they relied more on overseas export. On the other hand, a reduction in trade barriers will benefit tradable firms relatively more because their potential for international trade is larger.

Clearly, shipping costs only capture one aspect of exposure to shifts in trade policy. While it captures a structural economic feature of an industry that gives rise to a natural trade barrier, other hurdles such as time to ship, information barriers, or contract enforcement costs are not captured (Barrot, Loualiche, and Sauvagnat, 2019). Another important drawback is that shipping costs are only available for goods. Therefore, the measure does not apply to firms in service sectors.

Export Share

For the second characteristic we follow Tian (2018) and use data from input-output tables. Specifically, we download annual input-output tables from the OECD website for all available countries and sectors. From these tables, we obtain the value of exports and the value of the total output per sector-country pair. Using this data, we compute the export share of a sector *s* as follows[10].

$$Export\ share_s = \frac{\sum_c Exports_{s,c}}{\sum_c Output_{s,c}}$$

In the equation above, *s,c* indicates a sector-country pair and the sums are taken across all countries. The export share captures the *realised* amount of exports in a given sector, as a percentage of the total output in that sector. As for shipping costs, every June, a stock is assigned the export share value of the sector to which it belongs[11] based on data of the previous year[12].

The export share captures the realised level of international trade, whereas tradability captures the *potential* for international trade. An increase in trade barriers will impose extra costs on firms in sectors which rely on exports for a big share of their output, while having less of an impact on non-exporting sectors. Therefore, firms in sectors with a high export share are expected to suffer more from increased trade barriers. Conversely, trade liberalisation will reduce costs for firms in sectors with a high export share while not having much impact on domestic sectors.

A benefit of this measure is that it is available for an exhaustive set of sectors that covers the full universe. However, this coverage comes with the cost that the sector grouping is somewhat coarse. The OECD sector classification distinguishes between only 36 sectors[13]. Given that the literature has documented substantial heterogeneity in firm outcomes within industries as a result of trade liberalisation (e.g., Bernard, Jensen, and Schott, 2006), it is clear that using only the export share characteristic as a measure of exposure to shifts in trade policy would not be optimal. The information contained in the export share should therefore be complemented with other measures.

10 - De Gregorio, Giovannini, and Wolf (1994) and Lombardo and Ravenna (2014) construct a similar measure, but also include the value of imports in the numerator. We follow Tian (2018) and include only export. Since the OECD data includes many countries, it should be representative for the global volume of international trade. Globally, total imports and exports for a sector correspond. Therefore, including imports next to exports should not add much information in terms of the ranking of each sector according to this measure. We have confirmed this is the case in our data (see results in the appendix).
11 - As for shipping costs, we first map the OECD sectors to NACE codes to link them to our universe. OECD sectors aggregate industries using the ISIC classification, so we can use the publicly available industry mappings from ISIC to NACE.
12 - Because we have OECD input-output tables from 2005 to 2015, following June 2016 we assign to stocks the export share value of the industry based on the most recent available year (which is 2015).
13 - This compares with 81 sectors for which we have distinct values of shipping costs, meaning that the level of granularity of export share is less than half than the one that we have for tradability.

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Risk Disclosures

The third characteristic is based on 10-K risk disclosure data. Following Hassan et al. (2019) and Caldara et al. (2020), we use textual analysis to extract exposures from text data. We first obtain annual 10-K filings for the firms in our universe by web scraping the SEC's EDGAR system and extract the text in section 1A 'risk factors' from each filing. Using this risk disclosure text, we construct a measure of exposure to shifts in trade policy via a dictionary-based approach. Our trade dictionary is based on the trade-specific keywords proposed by Baker, Bloom, and Davis (2016) and Caldara et al. (2020). It contains 23 keywords, such as *tariff*, *import duty*, and *trade policy*. The full list is shown in the appendix. The measure is defined as the fraction of words in the risk disclosures that are in the trade dictionary.

$$Risk\ disclosures = \frac{\sum_{w}^{W_T}(1_{w\in keywords})}{W_T}$$

In which, W_T is the total number of words in a firm's risk disclosures and $1_{w\in keywords}$ takes the value of 1 when word w is in the trade dictionary and 0 otherwise. Manual validation checks of the text captured by the dictionary pointed out that the keyword *tariff* is often used in a context not related to international trade by telecom and utility firms. Consequently, *tariff* is omitted from the dictionary when calculating the risk disclosures score for firms in these sectors. Details on this procedure, including data collection, text preprocessing, validation checks, and tests with alternative specifications can be found in the appendix. Central Index Keys (CIK), the firm identifiers from EDGAR, are linked to our stock universe via tickers, using the mapping provided by the SEC[14]. Every June, each stock is assigned the risk disclosures exposure score based on the text from its most recent 10-K filing.

Risk disclosures are a useful complement to the other two exposure measures. Firms are legally required to disclose material risks in their annual 10-K filings. Litigation risk thus incentivises them to provide a comprehensive overview of the risks they face. Furthermore, these disclosures should be forward-looking, which is particularly useful for our purpose of creating a measure that allows to capture risk exposures out-of-sample. Campbell et al. (2014) find that 10-K risk disclosures tend to be firm-specific and reflect the type of risks that a particular firm faces[15]. This alleviates concerns that these official disclosures are mostly boilerplate language. Therefore, we expect that firms devoting a lot of attention to the discussions related to trade policy in their risk disclosures will be more sensitive to corresponding changes. Based on extensive validation readings of the text fragments that we capture, described in the appendix, the disclosures mostly indicate that an increase in trade barriers would be harmful for the firm. Consequently, a higher fraction of risk disclosures devoted to trade policy is interpreted as indicating that the firm will suffer more due to an increase in trade barriers.

A benefit of the risk disclosures measure compared to tradability and export share is that it is available at the firm-level. It also has the potential to capture any channel via which changes in trade barriers can influence a firm, as long as analysts and management pay attention to such a

14 - See https://www.sec.gov/include/ticker.txt
15 - Beatty, Cheng, and Zhang (2019) give a note of caution here, arguing that the risk disclosures became less reflective of the underlying economic risks over time after the financial crisis of 2008.

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channel. These benefits do come with the drawback that it is potentially noisier. As opposed to the fundamental economic features of a firm or industry captured by tradability and export share, risk disclosures contain a subjective assessment of the risks faced by the firm. Transforming the text into a numerical score also adds a layer of noise. Furthermore, a substantial fraction of firms in our sample does not mention any terms from our trade dictionary. Consequently, the risk disclosures measure is not able to distinguish between these firms.

We obtain annual exposures according to each dimension (the tradability, export share and risk disclosures measure) at each June between 2006 and 2019. Our data starts in 2006 because the SEC introduced the requirement to include section 1A 'risk factors' in 10-K reports for fiscal years ending after 1 December 2005. Exhibit 2 presents the average coverage and cross-sectional distribution of each of the measures over time. Tradability values are only available for around 39% of the stocks in our universe since shipping costs are not available for services. The majority of the firms for which we do have a tradability value incur shipping costs for their products between 1% and 5%. As mentioned above, export shares are available for nearly all stocks in our universe. There is a wide dispersion in export shares, with a 20th percentile value of 8.1% and an 80th percentile value of 31.5%. The summary statistics for risk disclosures show that we are able to obtain the required data for around 92% of our sample. The 20th percentile value of 0% indicates that, in all years, at least 20% of the firms do not mention any of the terms in our trade dictionary. In most years, this number is even above 40%. As a further description of what each of these measures captures, we show the industries with the highest and lowest tradability and export shares in the appendix, together with a sample of text fragments that are captured by the risk disclosures measure.

Exhibit 2: Summary statistics
The table shows the coverage and cross-sectional distribution of the tradability, export share and risk disclosures measures. The cross-sectional distribution ignores any missing values. These values are calculated every June between 2006 and 2019 and the table shows the time-series averages. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Summary statistics	Coverage	Minimum	20th percentile	40th percentile	60th percentile	80th percentile	Maximum
Tradability	39%	1.1%	1.7%	2.5%	3.3%	4.8%	20.3%
Export share	98%	0.2%	8.1%	9.4%	14.3%	31.5%	45.1%
Risk disclosures	92%	0.00%	0.00%	0.00%	0.01%	0.04%	0.49%

Information from Stock Return Covariances

Apart from the tradability, export share and risk disclosures measures described above, which we will refer to as characteristics from now on, we also add returns-based information to our multi-dimensional exposure measure. We do this by constructing mimicking portfolios based on each characteristic. These portfolios go long stocks with a high characteristic score and short stocks with a low characteristic score. Since the characteristics carry information on trade policy risk, these portfolios reflect the corresponding risk exposures. A measure of the covariance between each stock's returns and these mimicking portfolios is therefore a market-based measure of exposure to the trade policy risk dimensions represented by the characteristics. The covariance measures

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capture whether a stock behaves similar as stocks with a high characteristic score and therefore tease out information about exposures that is firm specific and available for all firms, even those without observed characteristics. This additional information is an important complement to the characteristics proposed by earlier research.

The goal of the mimicking portfolios is to create a time series that captures the difference in return between stocks with a high characteristic score and stocks with a low characteristic score. For tradability, we construct an equal-weighted portfolio of all stocks with shipping costs that are higher than or equal to the 80th cross-sectional percentile value and an equal-weighted portfolio of the stocks with shipping costs lower than or equal to the 20th percentile. The tradability mimicking portfolio goes long the low shipping costs portfolio and short the high shipping costs portfolio. We create similar equal-weighted portfolios based on the 80th and 20th percentile values of export share. The export share mimicking portfolio goes long the high export share portfolio and short the low export share portfolio. For risk disclosures, the large fraction of stocks with a zero score means taking the stocks below the 20th percentile isn't suitable. Therefore, the mimicking portfolio simply goes long an equal-weighted portfolio of all stocks that mention at least one term in the trade dictionary and goes short an equal-weighted portfolio of all stocks that do not mention any trade term. We thus create three mimicking portfolios for which we have daily returns starting in June 2006. All portfolios are rebalanced annually in June.

Then, we estimate the covariance score for each stock in the universe with respect to each of the mimicking portfolios. These covariance scores aim to capture whether a stock's returns behave similar as a typical stock with a high characteristic score. The first step in this estimation is to regress the returns of a stock in excess of the risk-free rate on the returns of one of the mimicking portfolios, while controlling for the market return in excess of the risk-free rate.

$$R_t^i = \alpha^{i,m} + \gamma^{i,m} * MKT_t + \beta^{i,m} * MIM_t^m + \varepsilon_t^{i,m}$$

R_t^i is the excess return on stock *i* on day *t*, MKT_t is the excess return on a cap-weighted portfolio of all stocks in the universe on day *t*, and MIM_t^m is the return on mimicking portfolios *m* on day *t*. Every June, this regression is estimated for each stock-mimicking portfolio pair, based on the most recent two years of daily returns . This means we estimate 3,000 $\hat{\beta}^{i,m}$ values every June, for 1,000 stocks *i* and three mimicking portfolios *m*.

The second step to create the covariance score is to apply Bayesian shrinkage to all $\hat{\beta}^{i,m}$ values (Vasicek, 1973). In June of year *y*, the covariance score for each of the three dimensions *m* for each stock *i* is calculated as follows.

$$Covariance_y^{i,m} = \beta_y^{m,prior} * \frac{\sigma_{y,i,m}^2}{\sigma_{y,i,m}^2 + \sigma_{y,m}^2} + \hat{\beta}_y^{i,m} * \left(1 - \frac{\sigma_{y,i,m}^2}{\sigma_{y,i,m}^2 + \sigma_{y,m}^2}\right)$$

$\beta_y^{m,prior}$ is the average of the $\hat{\beta}_y^{i,m}$ values, averaged across all stocks *i*, $\sigma_{y,i,m}$ is the standard error of the estimated $\hat{\beta}_y^{i,m}$, and $\sigma_{y,m}$ is the standard deviation of the $\hat{\beta}_y^{i,m}$ values, across all stocks *i*.

16 - We require at least 70% of valid observations over the most recent two years to do the estimation.

2. Measuring Exposure to Shifts in Trade Policy

We obtain these covariance scores for every June from 2008 until 2019. This data starts two years after the characteristic scores since we require two years of mimicking portfolio returns for the estimation. In the appendix, we show that these covariance scores are robust out-of-sample.

A Combined Measure of Exposure

The covariance measures extract information from stock market returns. To the extent that market participants draw on a wide range of data sources for their trading decisions, they incorporate information that goes beyond what can be captured by the data used to construct the tradability, export share, and risk disclosures characteristics. Therefore, the covariance measures capture information on trade policy exposure beyond the information in characteristics alone.

Covariances also offer some more practical advantages compared to the characteristics, since they are available at the firm level for all stocks in the universe (as long as they have a sufficient return history for estimation). In contrast, tradability and export share are based on data at the level of granular industries rather than individual firms. The information content of risk disclosures is limited by the large proportion of firms that do not mention trade policy terms in their disclosures. Using characteristics alone therefore does not allow to make fine grain distinctions between firms' exposure to shifts in trade policy. Furthermore, shipping cost data, and to a lesser extent risk disclosures, are not available for all stocks in the universe. The covariance measures are directly available at the firm level and thus allow for granularity and high coverage. These features are desirable for applications. For example, when managing sensitivity to shifts in trade policy in an equity portfolio, the investor would need information on all firms in the market.

We incorporate the advantages of the market-based covariances in our exposure measure by augmenting the characteristics. For tradability, export share, and risk disclosures, we first rank each stock in the universe according to the characteristic and covariance score independently. Any tied values are given the average rank of these values and missing values are assigned the median rank. Note that for the tradability characteristic, we assign ranks in the opposite direction, since low shipping costs indicate a negative sensitivity to an increase in trade barriers. We then define augmented scores for tradability, export share, and risk disclosures, as the average of the respective characteristic and covariance rank for the stock[17].

The augmented scores are available for all stocks in the universe, granular and well-distributed. We replace missing characteristics with the median rank in the universe, which means we avoid giving particularly high or low ranks to firms with missing information. Since the covariance scores are unique for each stock, we also avoid the lack of granularity of the export share and risk disclosure characteristics.

We expect that combining the information in the augmented tradability, export share, and risk disclosures measures will improve our ability to capture a firm's exposure to shifts in trade policy.

17 - In the end, we are interested in how a stock reacts to a change in trade policy, so using only the returns-based covariance scores may also seem appealing. However, an extra layer of estimation risk is introduced when obtaining the covariance scores. Therefore, we give an equal weight to the more fundamental information in the characteristics as an additional form of shrinkage. In the appendix, we show that our main results are similar when using only covariances, but that most estimates have larger standard errors.

2. Measuring Exposure to Shifts in Trade Policy

These shifts impact firms via multiple channels. High trade barriers reduce export possibilities, foreign competition (Bernard et al., 2003), and the availability of foreign inputs (Antràs, Fort, and Tintelnot, 2017). Tradability and export share potentially capture export effects, but not necessarily the input channel. Risk disclosures do not target one specific channel but have the potential to include information on all of them. The information content in the three measures is therefore complementary. Given the practical advantages introduced by the addition of the covariances, in terms of granularity and coverage, we can combine the three augmented scores in a straightforward manner by simply taking the equal-weighted average.

Exhibit 3 shows how all these different measures relate to each other. First, we select the top and bottom 30% of stocks based on the augmented score for each dimension and for the combined score. For each stock selection, we calculated the average of the exposure measures across all stocks it contains at a given point in time. We computed these exposure measures using the original characteristic, the covariance score related to the characteristic and the augmented score. This is done each year between 2008 and 2019, and the table shows the time-series averages. The reported exposure measures are standardised and thus can be interpreted as the distance from the cross-sectional average expressed in terms of standard error.

We highlight three key observations from this table. First, the augmenting procedure preserves the information content in both the characteristics and the covariances. When conditioning on high and low augmented tradability scores, the average tradability characteristic is 66% above and 69% below average, and the average tradability covariance is 95% above and 91% below average, respectively. For export share and risk disclosures these values are roughly similar. This means that our methodology successfully creates a well-distributed augmented measure that combines the information in the characteristics and covariances. Second, the three dimensions indeed seem to capture different information. For example, when conditioning on low augmented tradability scores, the average export share characteristic is around the average of the full universe. Similarly, the average tradability characteristic for stocks with a high augmented risk disclosure score is only 9% above the universe average. The export share and risk disclosures dimensions do seem more related to each other. Still, this indicates that combining the three dimensions can add value over using only a single one. Third, the combined exposure score is well-balanced in the sense that it captures the information from each dimension without giving an excessive weight to a single one. Stocks with a high combined exposure score have an average augmented tradability, export share, and risk disclosures score that is 74%, 92%, and 94% above the universe average, respectively. Similarly, stocks with a low combined exposure score have augmented scores that are on average 44%, 104%, and 102% below the universe average. The absolute values for the characteristics and covariances are a little lower in most cases, but still indicate that the combined score captures the information contained in each measure in a balanced way.

2. Measuring Exposure to Shifts in Trade Policy

Exhibit 3: Conditional average exposure measures
The table reports the conditional average values of the characteristic, covariance, and augmented scores for each of the tradability, export share, and risk disclosures dimensions. The averages are calculated for stock selections based on the condition indicated in the column headers, i.e., for stocks with either a high or a low augmented tradability, augmented export share, augmented risk disclosures, or combined exposure score. High and low selections are defined as stocks with a score higher than or equal to the 70th percentile, and lower than or equal to the 30th percentile, respectively. Every June between 2008 and 2019, each measure is first transformed to a z-score in the cross-section. Then the conditional averages are calculated. The values shown in the table are the time-series averages of these annual conditional averages. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Conditional average exposure measures		Tradability		Export share		Risk Disclosures		Combined	
		High	Low	High	Low	High	Low	High	Low
Tradability	Characteristic	66%	-69%	16%	-42%	9%	-23%	48%	-107%
	Covariance	95%	-91%	-14%	-6%	7%	-19%	46%	-36%
	Augmented	117%	-117%	10%	-10%	9%	-16%	74%	-44%
Export share	Characteristic	50%	-2%	116%	-89%	61%	-62%	92%	-75%
	Covariance	23%	4%	92%	-104%	57%	-82%	68%	-94%
	Augmented	36%	6%	119%	-121%	71%	-90%	92%	-104%
Risk disclosures	Characteristic	-5%	20%	37%	-38%	93%	-51%	49%	-43%
	Covariance	44%	-14%	73%	-99%	89%	-108%	86%	-106%
	Augmented	29%	3%	73%	-90%	127%	-115%	94%	-102%

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

So far, we have proposed a measure of exposure to shifts in trade policy and provided its economic motivation. We now want to test whether our ex-ante measure captures cross-sectional variation in reactions to trade policy shifts observed ex-post. We expect that firms with a high score will suffer relatively more when trade barriers increase, while firms with a low score will tend to benefit relatively more from an increase in trade barriers. To facilitate our discussion, we refer to firms with a high score as 'trade peace' firms, and firms with a low score as 'trade war' firms.

To test empirically whether our multi-dimensional score captures exposure to shifts in trade policy, we conduct an event study of reactions to trade policy events. Price reactions can be interpreted as an ex-post market-based measure of exposure[18]. Following an event that brings relevant economic news, market participants will update their expectations, and price reactions reveal changes in market expectations over future firm cashflows and/or risk[19]. Focusing on the period following the selected events allows us to link changes in market expectations to the common narrative that characterises the events, which in our case is a shift in trade policy. This means that price reactions to policy shifts represent an ex-post measure that captures market participants' assessment of exposure of firms to the policy shift. In practical terms, given that our hypothesis is that trade peace stocks stand to lose more than trade war stocks when governments raise barriers to international trade, we test whether the stock price reactions of trade peace stocks to these events are significantly more negative than those of trade war stocks.

First, we define event days on which there is a clear change in trade policy. In order to be useful for us, we need events which are important enough to influence stock prices. This is a first obvious condition to be able to estimate the impact of trade events on stock prices. We follow Amiti, Kong, and Weinstein (2020), who propose an objective method to define events. They use peaks in Google searches for the term trade war, which match with clearly identifiable changes in trade policy. To ensure that we use the most influential events, we focus on the tariff events that characterise the trade war between the US and China, the world's two biggest economies. Peaks in Google searches indicate that the events receive much attention. The assumption that stock prices should be influenced by them is therefore reasonable. Exhibit 4 presents the seven resulting event dates, together with a short description of the trade policy change.

Exhibit 4: Trade events
The events in the table are the US tariff events and Chinese retaliation events taken from Amiti, Kong, and Weinstein (2020).

Date	Event Description
01 March 2018	US announces steel and aluminium tariffs
22 March 2018	US orders identification of Chinese products for tariffs
02 April 2018	China to impose tariffs on 128 US exports
15 June 2018	China retaliates on USD50bn of US imports
17 September 2018	US announces tariffs on USD200 bn goods from China
10 May 2019	US raises tariffs from 10% to 25% on USD200bn of Chinese imports
23 August 2019	China raises tariffs on soy and autos

18 - This is similar to Greenland et al. (2020), although we emphasise that, as opposed to abnormal returns, our exposure measure is available ex ante and not purely empirical but based on fundamental economic mechanisms. See also Fisman, Hamao, and Wang (2014), Davies and Studnicka (2018), Egger and Zhu (2020) and Bianconi, Esposito, and Sammon (2021) for the use of event studies related to international trade.
19 - This follows from prices forming as the sum of the stock's discounted future expected cashflows.

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

We also need to specify the event window in which we expect the event to impact stock returns. The event dates define the moment when the news of a trade policy change reaches the market. Only analysing returns on this day, however, may not allow enough time for the market to fully adjust prices to the event. The event window should also not be too long since we want to avoid capturing price reactions to subsequent non-trade related news. Therefore, we define the main event window to include the event date and the subsequent seven calendar days. In the appendix, we show that conclusions are not sensitive to using event windows comprised of the event date and the subsequent day or the event date and the subsequent fourteen days instead. The length of these event windows is in a similar range as those used by Davies and Studnicka (2018) and Amiti, Kong, and Weinstein (2020).

Then, we want to estimate the stock-specific impact of the events on the share price during the event windows. To isolate the stock-specific component of the stock returns, it is necessary to control for the factors driving returns independent of the event. Therefore, we estimate a model for each stock's expected returns based on daily returns from one year before each event until one week before the event[20]. Our main results are based on the classic CAPM as the model for normal returns, but in the appendix, we show that conclusions are similar when using the Fama-French (2015) five-factor model.

$$R_t^i = \alpha^i + \beta^i * MKT_t + \varepsilon_t^i$$

R_t^i represents the returns of stock i at day t in excess of the risk-free rate and MKT_t is the return on the market factor.

For each day t in the event windows, we can then define the abnormal return AR_t^i for stock i as the difference between the realised return RR_t^i and the normal expected return NR_t^i. In the equations below, RF_t is the risk-free rate on day t and $\hat{\beta}^i$ is the estimated value of β^i above.

$$AR_t^i = RR_t^i - NR_t^i \text{, with } NR_t^i = RF_t + \hat{\beta}^i * MKT_t$$

Finally, the cumulative abnormal return CAR^i for stock i, over a given event window, is the sum of its abnormal returns on each day in that window[21]. Since the event windows are chosen as moments on which shifts in trade policy are expected to influence stock prices and market-wide returns are controlled for, the cumulative abnormal returns capture the stock-specific impact of trade policy shifts. Therefore, we interpret it as an ex-post measure of exposure to such shifts.

$$CAR^i = \sum_{t \in event\ window} AR_t^i$$

Our goal is to test whether our combined exposure measure, which is available before the events, is related to stock price reactions to the trade policy announcements, as estimated by the cumulative abnormal returns. A strong relation would validate our combined exposure measure. We analyse this relationship not only for the combined exposure measure, but also for the augmented tradability, export share and risk disclosures scores. The corresponding results will justify empirically why combining the different dimensions adds value.

20 - If the period from one year until one week before an event includes other event windows, we exclude these event windows from the data when estimating the model for normal returns.
21 - We follow standard practice in event study and take the sum of daily returns as opposed to the product of cumulative daily returns. This allows us to conduct standard hypothesis for arithmetic averages (i.e., a t-test). Given the short time span of events (a few days), the difference between the two ways of computing cumulative returns over the event window will be tiny.

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

A simple first test of this relationship is to compare the conditional average cumulative abnormal returns between trade peace and trade war firms. In this analysis, we define the 30% of firms with the highest and lowest exposure scores as trade peace and trade war firms. This selection is made as of the most recent June before each event date and the cumulative abnormal returns are pooled across events to calculate the conditional averages. Exhibit 5 presents the corresponding results, based on one of the augmented or combined exposure scores.

These results could be interpreted from the perspective of investors that want to manage trade policy risks via an equal-weighted trade peace or trade war portfolio. In this interpretation, the results roughly represent the excess returns on the portfolios during one of the event windows, after controlling for market exposures. The average cumulative abnormal returns of trade peace stocks formed based on the individual dimensions range from -0.4% to -0.6%, while these values for the trade war stocks range from 0.3% to 0.7%. Based on t-statistics that account for event-induced variance and correlation structures between stocks (Kolari and Pynnonen, 2010), results are mixed in terms of statistical significance. Using the combined scores to create the stock selections, trade peace stocks have an average cumulative abnormal return of -0.7% and for trade war stocks this is 0.7%. Both values are statistically significant. Therefore, the combined exposure score allows to create well-diversified portfolios that generate a return spread of 1.4% over the short event windows, which consist of only six trading days. This value is economically meaningful. It is more than 10 times the long-term average of the weekly returns of the US excess market returns[22]. The effect is also large in comparison to the pre-announcement impact of the FOMC meetings, another set of events for which the literature has documented an important impact on market's returns. For instance, Lucca and Moench (2014) estimate that the average abnormal return on S&P 500 observed in the hours before the FOMC announcements is 0.5%[23], which is similar in magnitude to the effect that we document for both the trade peace and the trade war portfolio. These results also show that the combined score adds value over the individual dimensions, since it results in a larger spread between trade peace and trade war stocks.

Exhibit 5: Conditional average cumulative abnormal returns on event days
The table reports conditional average cumulative abnormal returns and t-statistics (in brackets). Cumulative abnormal returns are based on the CAPM model to estimate normal returns and an event window from the event day until one week after the event. The event dates are 01/03/2018, 22/03/2018, 02/04/2018, 15/06/2018, 17/09/2018, 10/05/2019 and 23/08/2019. Stock selections are made based on the augmented tradability, augmented export share, augmented risk disclosures, or combined scores as of the most recent June before each event. Stocks with a score above or equal to the 70th percentile are trade peace stocks, stocks with a score below or equal to the 30th percentile are trade war stocks. The t-statistics are adjusted for event-induced variance and correlation across stocks, following Kolari and Pynnonen (2010). The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Conditional average cumulative abnormal returns on event days	Tradability	Export share	Risk disclosures	Combined
Trade peace stocks	-0.4%	-0.4%	-0.6%	-0.7%
	(-1.3)	(-1.5)	(-2.4)	(-2.8)
Trade war stocks	0.3%	0.7%	0.7%	0.7%
	(1.1)	(2.1)	(2.2)	(2.1)

22 - We estimate the average weekly excess equity market return in the U.S. using the data from the Kenneth French Data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) over the period from the 1st of July 1963 to the 30th of June 2020.
23 - Lucca and Moench (2014) shows that the effect of FOMC announcements accrues mostly in the hours preceding the announcement and it does not revert afterwards.

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

Next to the conditional averages, we also present results based on regressions with the cumulative abnormal returns as dependent variable, and the augmented and/or combined exposure measures as independent variables. The observations from the seven event dates are pooled together in one regression, after controlling for event-specific returns by de-meaning the cumulative abnormal returns per event. For each stock and each event, the augmented and combined exposure scores available as of the most recent June before the event date are linked to the cumulative abnormal return. These exposure scores are standardised to a z-score per event, to facilitate interpretation. Regression coefficients therefore indicate the expected impact on the cumulative abnormal return of a one standard deviation increase in the exposure score. Since stocks with a high exposure score are trade peace stocks and the events represent an increase in trade barriers, we expect the regression coefficients to be negative. Note that any differences in market exposures across stocks are controlled for via the construction of the abnormal returns.

Exhibit 6 shows the results of several specifications of these regressions. The first, second, and third specification use either the augmented tradability, export share, or risk disclosures scores as a single independent variable. All resulting coefficients are significantly negative, ranging from -0.3% to -0.5%. This shows that each of the individual dimensions contains relevant information to capture a firm's exposure to trade policy shifts. The fourth regression includes all three measures as independent variables. Importantly, these results show that each dimension contains relevant information beyond what is already captured by the other two. All three coefficients are still significantly negative, with a value of -0.3%. The adjusted R-squared of the regression also increases to 2.2% from 0.6%-1.7%, indicating that the three measures combined capture more of the variation in cumulative abnormal returns compared to each one individually. Based on regressions one to four, it clearly seems that combining the information in the three dimensions adds value. Next, we test whether the combined measure is constructed in a way that maintains this potential combined explanatory power. The results in the fifth column show that this is the case, with the same adjusted R-squared value as for regression four. The combined measure thus explains as much variation in cumulative abnormal returns as the combination of the three individual dimensions. The regression coefficient is again highly significantly negative at -0.6%. A one standard deviation increase in the combined exposure score corresponds to a cumulative abnormal return that is 60bp lower. The last three specifications test whether one of the individual dimensions can still add value once we control for the combined exposure score. However, the results in columns six to eight show that this is not the case. None of the coefficients for the individual dimensions is significantly different from zero, while the size of the coefficient for the combined score and the adjusted R-squared are unaffected. Together with the fact that all coefficients in regression four are the same size, this indicates that averaging the individual dimensions with an equal weight in the combined exposure score results in a measure that captures all relevant information in the three individual dimensions. To sum up, tradability, export share, and risk disclosures each contain useful information to explain differences in stock price reactions to trade policy announcements, and the combined measure successfully captures all this information.

3. Returns-Based Validation: Does the Measure Capture Heterogeneity of Stock Price Reactions to Trade Policy Shocks?

Exhibit 6: Relation between exposure scores and cumulative abnormal returns
The table reports the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of cumulative abnormal returns on augmented tradability, augmented export share, augmented risk disclosures, and/or combined scores. Cumulative abnormal returns are based on the CAPM model to estimate normal returns and an event window from the event day until one week after the event. The event dates are 01/03/2018, 22/03/2018, 02/04/2018, 15/06/2018, 17/09/2018, 10/05/2019 and 23/08/2019. Values for the independent variables as of the most recent June before each event are used. All event dates are pooled together in the regression, with cumulative abnormal returns de-meaned per event and regressors transformed to a z-score per event. The t-statistics are adjusted for heteroskedasticity. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Relation between exposure scores and cumulative abnormal returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tradability	-0.3%			-0.3%		0.0%		
	(-6.0)			(-4.8)		(0.2)		
Export share		-0.5%		-0.3%			0.0%	
		(-11.2)		(-3.6)			(0.2)	
Risk disclosures			-0.5%	-0.3%				-0.1%
			(-11.4)	(-4.4)				(-0.8)
Combined					-0.6%	-0.6%	-0.6%	-0.6%
					(-13.6)	(-13.5)	(-5.8)	(-6.9)
Adj. R-squared	0.6%	1.3%	1.7%	2.2%	2.2%	2.2%	2.2%	2.2%

4. Comparison with Standard Firm Classifications: Sector and Size Effects

4. Comparison with Standard Firm Classifications: Sector and Size Effects

In the previous section, we have shown that the combined exposure score indeed captures exposures to shifts in trade policy. In this section, we further show that it is also preferable over some plausible alternatives. Tradability, export share and risk disclosures are proposed to specifically target exposure to shifts in trade policy. On the other hand, one could hypothesise that more standard firm classifications, such as size or sector portfolios, would work equally well to capture variation in exposure to shifts in trade policy.

The relation between firm size and how it is impacted by a change in trade barriers is documented in the literature (e.g., Melitz, 2003). A reduction in trade barriers tends to benefit larger firms while hurting smaller ones. To add practical value in capturing exposures, however, this effect still needs to be important once we control for our proposed measures. Likewise, stocks in certain sectors may be hurt more by an increase in trade barriers than others. As we graphically show in the appendix, for example, industrial or technology firms are more exposed to foreign trade than financial or utility firms, according to our combined measure. Again, relevant questions are whether a tilt towards these broad sectors is more efficient to capture the same information as the three dimensions in our combined measure, or whether sector membership still adds value once controlling for that information.

In the spirit of Freyberger, Neuhierl, and Weber (2020), we use LASSO regressions to address these questions and select the variables that are most important to explain the variation in ex-post exposure to shifts in trade policy. LASSO regressions are a form of penalised regressions that tend to shrink coefficients of uninformative explanatory variables to zero. As such, they are useful to select the variables that are most informative to explain the variation in the dependent variable. Specifically, we use the following standard linear model to estimate the coefficients β_j.

$$\min_{\beta}\left(\frac{1}{2N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{K}x_{ij}\beta_j\right)^2+\lambda\sum_{j=1}^{K}|\beta_j|\right)$$

N is the number of observations, K is the number of explanatory variables, y_i is an observation of the dependent variable, x_{ij} is an observation of explanatory variable j, λ is the penalty parameter, and β_j is the regression coefficients of explanatory variable j. The first term in this expression corresponds to the sum of squared residuals that is minimised in a standard OLS regression. The second term adds a penalty that is proportional to the sum of the absolute values of the estimated coefficients, which shrinks them towards zero. A higher λ therefore results in more coefficients estimated to be zero.

As in our earlier analysis, we use the cumulative abnormal returns around tariff announcements as dependent variable, and the augmented and combined exposure measures as independent variables. In this case, we also add the log of a firm's market capitalisation and dummy variables indicating sector membership as independent variables. We define 10 sectors based on Refinitiv's top-level TRBC classification. Again, observations from the seven event dates are pooled together and cumulative abnormal returns are de-meaned per event. The values for the independent variables are the ones

4. Comparison with Standard Firm Classifications: Sector and Size Effects

available as of the most recent June before the event date and, apart from the sector dummies, they are standardised to a z-score per event. Since we want to test what the most relevant variables are to explain variation in the cumulative abnormal returns, we adjust the value of the λ parameter to allow for only one, two, or three non-zero coefficients. The variables corresponding to these non-zero coefficients are the ones that are most informative to capture the variation in ex-post exposure to shifts in trade policy, as proxied for by the cumulative abnormal returns.

Exhibit 7 presents the results of this analysis. First, we estimate the coefficients when omitting the combined exposure measure from the independent variables in regressions (1)-(3). These differ in the value of the λ parameter, with (1) having the highest value so that only one coefficient is non-zero and (3) having the lowest parameter so that three coefficients become non-zero. The results for specification (3) show that the augmented risk disclosure, export share, and tradability scores are selected as being the most relevant. This indicates that the three individual dimensions in our combined measure are more important to capture the desired exposures than firm size or sector membership. Furthermore, the increase in adjusted R-squared from 0.9% to 1.3% and 1.9% when going from regression (1) to regression (2) and (3) shows that each dimension adds explanatory power. This is in line with the conclusions from Exhibit 6. Second, in regressions (4)-(6) we do the same analysis but now include the combined score. The results in column (4) show that the combined score is more important than any of the sector dummies or firm size to explain variation in cumulative abnormal returns. When reducing the penalty parameter λ, the dummy variables for the energy and non-cyclical consumer sectors become non-zero, as shown in columns (5) and (6). This sector information is therefore the most relevant once controlling for the combined exposure score. However, the adjusted R-squared values do not increase materially by the inclusion of these additional explanatory variables. This indicates that none of the variables included in the regression contain much relevant information to capture exposure to shifts in trade policy beyond what is captured by the combined exposure score.

To be clear, the results in Exhibit 7 do not indicate that firm size or sector membership do not contain useful information about exposure to shifts in trade policy. Rather, whatever information is contained in these variables is also captured by the combined exposure score. Furthermore, we show graphically in the appendix that there is substantial dispersion in the combined score within each of the broad sectors. It is therefore able to capture exposure beyond what is possible by simple sector tilts. For example, the healthcare sector includes both hospitals, whose business is inherently domestic, and pharmaceutical companies, which are more likely to have international operations. The export share and risk disclosures dimensions in the combined measure are able to capture these differences. Therefore, we conclude that the combined exposure score is preferred over the alternatives to capture exposure to shifts in trade policy.

4. Comparison with Standard Firm Classifications: Sector and Size Effects

Exhibit 7: Variable selection via LASSO regressions
The table reports the coefficients and adjusted r-squared values from LASSO regressions of cumulative abnormal returns on augmented tradability, augmented export share, augmented risk disclosures scores, and combined scores, next to firm size and sector dummies. Firm size is defined as the log of the firm's market capitalisation. Combined scores are not included in the first three columns. The penalty parameter is adjusted to allow for one, two or three non-zero coefficients. Cumulative abnormal returns are based on the CAPM model to estimate normal returns and an event window from the event day until one week after the event. The event dates are 01/03/2018, 22/03/2018, 02/04/2018, 15/06/2018, 17/09/2018, 10/05/2019 and 23/08/2019. Values for the independent variables as of the most recent June before each event are used. All event dates are pooled together in the regression, with cumulative abnormal returns de-meaned per event and regressors, apart from the sector dummies, transformed to a z-score per event. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Variable selection via LASSO regressions	(1)	(2)	(3)	(4)	(5)	(6)
Tradability	0	0	-0.1%	0	0	0
Export share	0	-0.1%	-0.1%	0	0	0
Risk disclosures	-0.2%	-0.2%	-0.3%	0	0	0
Combined	-	-	-	-0.5%	-0.5%	-0.5%
Size	0	0	0	0	0	0
Energy	0	0	0	0	0.1%	0.2%
Basic materials	0	0	0	0	0	0
Industrials	0	0	0	0	0	0
Cyclical consumer	0	0	0	0	0	0
Non-cyclical consumer	0	0	0	0	0	0.0%
Financials	0	0	0	0	0	0
Healthcare	0	0	0	0	0	0
Technology	0	0	0	0	0	0
Telecoms	0	0	0	0	0	0
Utilities	0	0	0	0	0	0
Adjusted R-squared	0.9%	1.3%	1.9%	2.1%	2.2%	2.2%

5. Sentiment-Based Validation: Does the Measure Capture Heterogeneity of Sentiment with Respect to Trade Policy Shocks?

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We propose a firm-level measure to capture exposure to shifts in trade policy and have so far shown its validity via ex-post observed abnormal returns around trade policy changes. Even though we show the robustness of results to some specification choices when estimating cumulative abnormal returns in the appendix, we still depend on parameters such as the selection of events. Furthermore, returns are noisy, especially during these relatively short time windows. Therefore, to increase our confidence that the measure captures a fundamental economic exposure, it is useful to test whether it can also explain variation in an alternative ex-post exposure measure. We perform similar regressions as those presented in Exhibit 6, but instead of using cumulative abnormal returns as the dependent variable, we now use sentiment regarding international trade extracted from a firm's earnings calls[24]. This alternative ex-post exposure measure is based on a completely different type of data than abnormal returns. Results similar to those reported in section 3 will therefore strongly support the conclusion that the combined score reliably captures exposures to shifts in trade policy.

To construct a firm-level measure of sentiment regarding international trade, we first collect all available quarterly earnings call transcripts for the firms in our universe from Refinitiv. Earnings calls typically include two sections. The firm's management will first provide a presentation discussing the previous quarter's results and their expectations going forward. Then, there is a Q&A section with external analysts. This data source therefore contains both internal and external perspectives on the issues facing the firm. From the transcript text, we want to extract an ex-post measure of exposure to shifts in trade policy. In order to do this, following Hassan et al. (2019), we assume that firms heavily impacted by changes in trade policy will devote a lot of time in their earnings call to discuss this. Further, we also assume that trade policy discussions with a positive connotation indicate that a firm is positively impacted by current changes in trade policy, while a negative connotation indicates the opposite. Note that in the construction of the risk disclosures characteristic, we implicitly assume that all topics discussed in a firm's risk disclosures impact the firm negatively. It does not seem reasonable to make the same assumption in the case of earnings calls, however, due to the different nature of this data source. Consequently, we aim to capture how much attention firms spend on trade policy in their earnings calls and whether these discussions have a positive or negative connotation.

Our analysis of sentiment from earnings call transcript data provides a true out of sample test of the exposure measure used to obtain ex ante information on trade policy exposure, since we do not use information from earnings call transcripts in constructing the ex-ante measure. Besides withholding data for an out of sample assessment there are more important reasons for why we do not include the textual data from earnings call transcript in our ex ante measure of exposure. As we will show below, analysis of earnings call transcripts shows large variation in the attention given to the trade policy topic over time, with very little attention in early parts of the sample. These variations in attention reflect that discussions between management and analysts tend to pick up topics of current interest and high media attention. The low attention to trade policy topics in earnings calls over earlier parts of the sample implies that it would have been close to impossible to obtain reliable information on exposure to trade policy risk ex ante. Text from risk disclosure at the firm level, which we use in ex ante measurement, does not display such an attention effect since firms provide a comprehensive

24 - Sentiment has also been used to study the heterogenous exposure to the impact of the Covid-19 outbreak in Ramelli and Wagner (2020).

5. Sentiment-Based Validation: Does the Measure Capture Heterogeneity of Sentiment with Respect to Trade Policy Shocks?

list of relevant risk exposures at each point in time. In ex post validation, the effects of time variation in attention are actually useful because one would expect high exposure firms to display negative sentiment ex post during periods when attention to trade policy sentiment from earnings call transcripts rises. We therefore see earnings call transcripts as a useful source for ex post validation but not for ex ante measurement.

A dictionary-based approach similar to the one we used to construct the risk disclosures characteristic is suitable to capture how much attention firms spend on trade policy in their earnings calls but does not capture the sentiment in these discussions. Therefore, we follow Hassan et al. (2019) in their definition of a measure that also aims to capture the sentiment surrounding a given topic.

$$Trade\ sentiment = \frac{\sum_{w}^{W_T}\left(1_{w \in keywords} * \sum_{c=w-10}^{w+10} S(c)\right)}{W_T}$$

W_T is the total number of words in an earnings call, $1_{w \in keywords}$ takes the value of 1 if the term w is in the trade dictionary and 0 otherwise, and $S(c)$ takes the value of +1 when c is in the positive word list from Loughran and McDonald (2011), -1 when c is in their negative word list and 0 otherwise. The trade dictionary is the same as the one used to construct the risk disclosures characteristic, based on the trade-specific keywords proposed by Baker, Bloom, and Davis (2016) and Caldara et al. (2020).[25]

This procedure gives us a quarterly, firm-level measure of trade sentiment, which we interpret as an ex-post proxy for firms' exposure to shifts in trade policy. A positive trade sentiment indicates that the firm is positively impacted by current changes in trade policy, a negative trade sentiment indicates the opposite. Details on the procedure to create the trade sentiment measure, including text preprocessing, validation checks, and tests with alternative specifications can be found in the appendix.

Before we do the regression analysis to test the relationship between our augmented or combined exposure scores and trade sentiment, it is important to point out that a specific earnings call tends to discuss a limited number of topics. In other words, not many firms will discuss trade policy when there are no big changes to discuss. Of course, in order to do a useful analysis, we require that a reasonably large sample of firms actually discuss trade policy in their earnings calls. Otherwise, the trade sentiment measure will automatically have a value of zero for most firms in the universe and will thus not be informative. Exhibit 8 highlights this point by showing the time series of a measure of trade policy attention, defined as the percentage of earnings call transcripts linked to firms in our universe that mention at least one term in our trade dictionary. In most quarters until 2016, only around 5% of firms seem to discuss trade policy in their earnings calls. There is a first sharp peak to around 20% in the first quarter of 2017, before a longer period of increased attention between the second quarter of 2018 and the first quarter of 2020. To ensure we have enough firms that discuss trade policy in our sample, the regression analysis will be based on trade sentiment data from the third quarter of 2018. This is when trade policy attention peaks at around 35%.

25 - Similar to how we proceeded when using corporate risk disclosures, we do not count mentions of the keyword tariff if they appear to be referring to regulated prices instead of import and export duties In particular, we do not count mentions of the keyword tariff when for telecom and utility firms, or when the word appears next to a set of exclusion terms indicating a context of regulated prices, as published by Caldara et al. (2020).

5. Sentiment-Based Validation: Does the Measure Capture Heterogeneity of Sentiment with Respect to Trade Policy Shocks?

This period of increased attention coincides with the tariff announcements on which our event study is based, i.e., the midst of the US-China trade war. Therefore, we characterise this period as a period of increasing trade barriers. Consequently, in the third quarter of 2018, trade peace firms are expected to have a relatively more negative trade sentiment and trade war firms are expected to have a relatively more positive trade sentiment. In other words, the regression coefficients of trade sentiment on the augmented and combined exposure scores are expected to be negative.

Exhibit 8: Trade policy attention in earnings calls
The graph shows the percentage of earnings calls that mention at least one term in our trade dictionary, in each quarter from Q3 2008 until Q2 2020. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

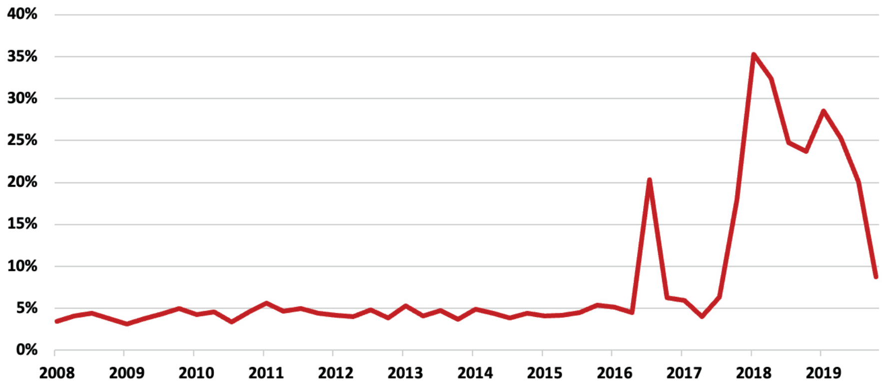


Exhibit 9 presents the results for regressions of trade sentiment in the third quarter of 2018 on different measures of firm-level exposure to trade policy risk. Note that the augmented and combined scores are estimated ex-ante, as of June 2018, while sentiment plays out over the following quarter. Both dependent and independent variables are transformed to a z-score, so the coefficients can be interpreted as the expected number of standard deviations increase in trade sentiment for a one standard deviation increase in exposure score.

The results in Exhibit 9 show a significant negative relation between the combined measure of trade policy exposure and trade-related sentiment. This finding implies that stocks identified as risky according to the combined measure face low sentiment in times of negative trade policy events, as would be expected. More precisely, the fifth column shows that the combined exposure score has a significantly negative coefficient. A one standard deviation increase in the combined score decreases the expected trade sentiment by around 10% of a standard deviation. However, the findings in Exhibit 9 also show that the expected relationship is not confirmed for all of the single dimensional exposure measures. The first three columns show that, while the augmented export share and risk disclosure scores have a significantly negative coefficient, the coefficient for augmented tradability is insignificant. These results suggest that using tradability alone, even though this is commonly done in the literature (e.g., Barrot, Loualiche, and Sauvagnat, 2019), does not necessarily allow to capture trade-related sentiment. Combining the different single measures avoids this weakness of the tradability measure.

5. Sentiment-Based Validation: Does the Measure Capture Heterogeneity of Sentiment with Respect to Trade Policy Shocks?

Exhibit 9 : Relation between exposure scores and trade sentiment
The table reports the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of trade sentiment in earnings calls on augmented tradability, augmented export share, augmented risk disclosures, and/or combined scores. The analysis is based on earnings call transcripts from Q3 2018 and exposure scores available in June 2018. All variables are transformed to a z-score. The t-statistics are adjusted for heteroskedasticity. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Relation between exposure scores and trade sentiment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tradability	3.4%			6.1%		13.1%		
	(1.0)			(1.6)		(2.9)		
Export share		-11.4%		-4.0%			-8.3%	
		(-3.3)		(-1.3)			(-2.0)	
Risk disclosures			-14.0%	-12.9%				-17.5%
			(-3.5)	(-2.9)				(-2.5)
Combined					-10.4%	-17.8%	-4.0%	4.2%
					(-2.9)	(-3.7)	(-0.9)	(0.7)
Adj. R-squared	0.01%	1.20%	1.86%	2.17%	0.98%	2.10%	1.16%	1.81%

6. International Data

6. International Data

We next show that the combined exposure score is also useful to capture exposure to shifts in trade policy in an international stock universe. The results we have presented so far are all based on US data. Obtaining similar results with a completely different dataset would again strengthen our confidence that we capture reliable economic mechanisms that will also be relevant going forward. In this section, we use data from Canada, countries in developed Europe, and countries in developed Asia Pacific. In total, we select a universe of around 1,000 of the largest and most liquid firms in this region to form a good representation of the investable stock universe in the developed world outside the US.[26]

We define firms' tradability and export share characteristics in the same way as for US firms, as described above. Even though shipping costs are based on data from the US Census Bureau, it is reasonable to use the same values for other developed countries. The ranking of goods in terms of shipping cost is not expected to materially differ depending on the countries between which they are shipped. Indeed, Barrot, Loualiche, and Sauvagnat (2019) point out that shipping costs are tightly linked to the weight-to-value ratio of goods, which is clearly independent from the shipping route. Export share is based on data from multiple countries, as the definition above shows, so it is representative for our international universe. A big difference compared to US data, however, is that 10-K risk disclosures are only available for US firms. We have experimented whether it is possible to capture the desired ex-ante exposures from earnings call transcripts instead. As highlighted by Exhibit 8, trade policy is not often discussed when no big changes occur, so we concluded that this is not a feasible option. Therefore, our international exposure scores are only based on the tradability and export share dimensions. We augment the tradability and export share characteristics in mostly the same way as for the US firms. The only difference is that we use weekly instead of daily returns when estimating a stock's exposure to the mimicking portfolios, because of asynchronous returns in our international universe. The combined exposure score is defined as the average of the augmented tradability and export share scores.

For the US data, we have shown that the combined measure captures exposure to shifts in trade policy, using abnormal returns around events that characterise the trade war between the US and China as an ex-post proxy for these exposures. Of course, these events are less relevant for our international universe since neither US nor Chinese firms are included. To be able to do a similar analysis, we use the trade war timeline made available by the Peterson Institute for International Economics to define a set of relevant events[27]. This timeline is based on a classification in five different battles. We focus on the one that is most relevant for the countries included in our international data, which is the series of actions around steel and aluminium. From all the events described there, we select all tariff announcements or the end of tariff exemptions that concern countries in our data. Furthermore, we decide to add the date of the Brexit referendum as a relevant event, following Davies and Studnicka (2018). The decision of the UK to leave the EU reduced confidence in the free trade agreements in place within the developed Europe region and increases the possibility of future trade barriers arising. Exhibit 10 gives an overview of the selected events, which involve the countries and regions in our international universe.

26 - We use data for the Scientific Beta Developed ex-US universe. The detailed construction process for this universe can be found in documentation accessible via www.scientificbeta.com.
27 - See https://www.piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide. We use the version updated as of 13/03/2020.

6. International Data

Exhibit 10: Trade events for international data
The 2018-2020 events in the table are based on the trade war timeline from Peterson Institute for International Economics.

Date	Event Description
23 Jun 2016	UK votes to leave the EU in referendum
1 Mar 2018	US announces steel and aluminium tariffs
1 Jun 2018	US ends tariff exemptions for EU, Canada, and Mexico
22 Jun 2018	EU retaliates with tariffs on US goods
1 Jul 2018	Canada imposes tariffs on US products
24 Jan 2020	US broadens steel and aluminium tariffs

For all stocks in the universe, we then obtain cumulative abnormal returns around these six events in mostly the same way as described for the US data. In this case, however, we estimate the CAPM model for normal returns using the past two years of weekly returns to account for asynchronous returns in our international universe. Abnormal returns on days around the event dates are then defined as the difference between realised and normal returns. Finally, the cumulative abnormal return is the sum of abnormal returns from the event date until one week after the event. Based on these cumulative abnormal returns as dependent variable, we run similar regressions as those shown in Exhibit 6. The observations at each event date are again pooled together, after de-meaning the cumulative abnormal returns per event. The augmented tradability, augmented export share, and combined scores available at the most recent June before each event date are used and standardised to a z-score per event.

Exhibit 11 shows the results of the analysis on international data. The first two columns show that tradability and export share are both significantly negatively related to the cumulative abnormal returns, as expected. As shown in column four, the combined score also has a significantly negative coefficient. A one standard deviation increase in the combined score corresponds to a cumulative abnormal return that is on average 40bp lower. The significantly negative relationship between abnormal returns and the combined score supports the conclusion that our proposed measure is suitable to capture exposure to shifts in trade policy out-of-sample.

Exhibit 11: Relation between exposure scores and cumulative abnormal returns - International universe
The table reports the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of cumulative abnormal returns on augmented tradability, augmented export share, and/or combined scores. Cumulative abnormal returns are based on the CAPM model to estimate normal returns and an event window from the event day until one week after the event. The event dates are 23/06/2016, 01/03/2018, 01/06/2018, 22/06/2018, 01/07/2018, and 24/01/2020. Values for the independent variables as of the most recent June before each event are used. All event dates are pooled together in the regression, with cumulative abnormal returns de-meaned per event and regressors transformed to a z-score per event. The t-statistics are adjusted for heteroskedasticity. The universe consists of around 1,000 of the largest and most liquid firms in a region consisting of Canada, developed Europe, and developed Asia-Pacific.

Relation between exposure scores and cumulative abnormal returns - International universe	(1)	(2)	(3)	(4)	(5)	(6)
Tradability	-0.1%		-0.1%		0.3%	
	(-2.0)		(-1.3)		(3.9)	
Export share		-0.4%	-0.4%			-0.3%
		(-7.6)	(-7.5)			(-3.9)
Combined				-0.4%	-0.6%	-0.1%
				(-6.9)	(-7.7)	(-1.3)
Adj. R-squared	0.0%	1.0%	1.0%	0.8%	1.0%	1.0%

7. Applications

7. Applications

Our proposed firm-level measure of exposure to shifts in trade policy can be useful to address various research questions. In this section, we highlight potential applications. This section is meant to provide illustrative examples rather than an exhaustive list or thorough investigation. First, the measure could be used to assess whether trade policy risk is priced. Second, it has practical use as a tool to construct portfolios that benefit investors who are exposed to shifts in trade policy via other components of their wealth, such as human capital. Third, shifts in trade policy benefit certain sectors in the economy while hurting others. Our exposure measure can be used to analyse the importance of such reallocation effects in the economy. The aim of this section is to point to interesting questions that could be addressed in future research via our exposure measure.

Asset Pricing

Several papers have analysed the question whether exposure to international trade carries a risk premium. Barrot, Loualiche, and Sauvagnat (2019) find that firms in low shipping cost industries carry a risk premium. They explain their finding with the higher risk of import competition that such firms face. Hoberg and Moon (2019) measure the extent of foreign sales or purchases from text in 10-K filings. They find that selling output abroad is related to higher stock returns, while firms sourcing inputs internationally have lower stock returns. They conclude that exposure to aggregate quantity shocks in the global trade network is a source of priced risk.

Our approach to measure exposure to shifts in trade policy can add value to this literature. For example, the conclusions of Barrot, Loualiche and Sauvagnat (2019) are based on a sample of only manufacturing firms since data on shipping costs is only relevant and available for this sector of the economy. In contrast, our measure of trade policy exposure is based on different characteristics, including shipping costs, realised international trade, and risk disclosures, augmented with information from stock return covariances. This allows us to capture different aspects of the exposure to trade policy shifts for a representative set of firms including the service sector.

The results in Exhibit 3 above indeed support the notion that our three dimensions capture different information, as stock rankings according to each dimension vary considerably. Each individual exposure measure may include some noise. To the extent that this noise is uncorrelated across our three dimensions, the combined exposure score reduces its impact. Exhibit 5 above shows that the combined score creates the largest spread in average cumulative abnormal returns, which supports that this measure more accurately captures exposure to shifts in trade policy than the individual dimensions.

To illustrate how our exposure measurement can be useful in asset pricing tests, we assess whether trade policy factors created using our exposure scores carry a premium. We construct a long-short 'trade peace' minus 'trade war' factor based on each of the tradability, export share, and risk disclosures dimensions, as well as based on the combined score. These factors go long a cap-weighted portfolio of the 30% of firms with the highest respective score, and short a cap-weighted portfolio of the 30%

of firms with the lowest score. For each of these factors, we calculate the average standalone return, as well as the alphas from the CAPM and the Fama French (2015) five-factor model. Positive average returns or alphas would point to the existence of a premium for firms that suffer relatively more from an increase in trade barriers.

Exhibit 12 presents the corresponding results. The values for the trade policy factor based on the augmented tradability score confirm the results from Barrot, Loualiche, and Sauvagnat (2019). High tradability, or low shipping cost, firms carry a premium. However, none of the other results are significantly different from zero for the factors based on the export share and risk disclosures dimensions. When combining the three dimensions into a single measure of trade policy exposure, we do not find evidence for a significant premium in this sample.

Of course, our analysis is limited and relies on a relatively short sample, so we do not aim to draw any strong conclusions based on these results. Exhibit 12 does point to interesting questions that can be addressed with our exposure measure. We have shown that each of the three dimensions and the combined score capture exposure to shifts in trade policy. However, they do not lead to similar results in terms of observed premia. Future research could assess whether the differences in premia are robust when considering other types of asset pricing tests and provide economic explanations for these differences. It would also be interesting to test more thoroughly whether results in previous work are robust to using these different types of measures. Our exposure measure allows to address this type of questions.

Exhibit 12: Performance of trade peace minus trade war factors
The table shows the standalone returns, CAPM alpha, Fama French five-factor alpha, and the corresponding t-statistics (in brackets) for trade peace minus trade war portfolios based on each of the augmented tradability, augmented export share, augmented risk disclosures, and combined scores. Trade war portfolios are composed of all stocks with a score below or equal to the 30th percentile. Trade peace portfolios are composed of all stocks with a score above or equal to the 70th percentile. Portfolios are rebalanced annually in June and cap-weighted. The results are based on daily returns from 30 June 2008 until 31 December 2019. Returns and alphas are annualised. The t-statistics are adjusted for heteroskedasticity and autocorrelation. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq. Data for the factors is obtained from the French data library.

Performance of trade peace minus trade war factors	Tradability	Export share	Risk disclosures	Combined
Standalone return	4.9%	-3.0%	3.3%	1.5%
	(2.0)	(-0.6)	(1.2)	(0.7)
CAPM alpha	5.8%	-2.3%	3.1%	2.1%
	(2.1)	(-0.6)	(1.0)	(0.7)
Fama French five-factor alpha	7.3%	-5.8%	1.1%	0.2%
	(2.8)	(-1.8)	(0.5)	(0.1)

Portfolio Choice

As emphasised by Cochrane (2022), portfolio theory must be all about heterogeneity since the average investor holds the market portfolio. Investors may have specific hedging needs in their financial portfolio due to exposures in outside income and liability streams, which leads them to deviate

7. Applications

from the market portfolio. For example, Eiling (2013) shows that investors should allocate different weights to industries in their optimal hedging portfolio depending on the industry in which they are employed[28]. Similarly, investors whose income has a higher or lower than average sensitivity to international trade may want to deviate from holding the market portfolio to hedge this exposure.

Our combined exposure measure allows to assess the extent to which an investor should optimally deviate from the market portfolio due to trade policy exposures in other parts of wealth. Furthermore, it allows to implement these ideas in practice by constructing a portfolio that allows to hedge this risk. We show that our measure captures stocks' exposures to shifts in trade policy out-of-sample, which is of key importance in portfolio choice problems. The exposure score is also granular and available for all stocks in an investment universe, which further facilitates its use in practice.

We provide a stylised illustration of this application, in which we show the optimal allocation to a long-short portfolio that hedges trade policy risk for investors with different sensitivities to this risk in their labour income. We consider investors who aim to maximise expected utility of wealth at the end of a single period, with wealth composed of an equity portfolio and accumulated labour income. Investors are assumed to be fully invested in the equity market portfolio and need to decide how far to deviate from this via an additional investment in a dollar-neutral trade war minus trade peace portfolio. The parameters in this illustration are chosen to represent a typical US household and use the results in Exhibit 5 to model the portfolio's ability to hedge shifts in trade policy. Full details regarding the underlying assumptions and parameters are described in the appendix.

Exhibit 13 graphically shows the corresponding results. The x-axis represents a range of investors that differ in the sensitivity of their labour income to shifts in trade policy. The values on this axis represent the change in labour income during a year in which there are considerable trade tensions (comparable to those observed in our sample during the years 2018 or 2019). The blue line shows the weight that each investor optimally invests in the trade war minus trade peace portfolio and the red line is an indication of how much the existence of this portfolio benefits these investors. It shows the difference in the ratio of expected final wealth over its standard deviation between the optimal allocation and a zero allocation to the long-short trade policy hedging portfolio. By construction, the optimal weight shows that investors whose labour income suffers from an increase in trade barriers should hedge this exposure via a long position in the trade war minus trade peace portfolio, which performs well during an increase in trade barriers. Investors with the opposite exposure in labour income, on the other hand, can use a short position in the portfolio as a hedge. The red line shows that investors with a stronger labour income sensitivity benefit more from the availability of a hedge portfolio.

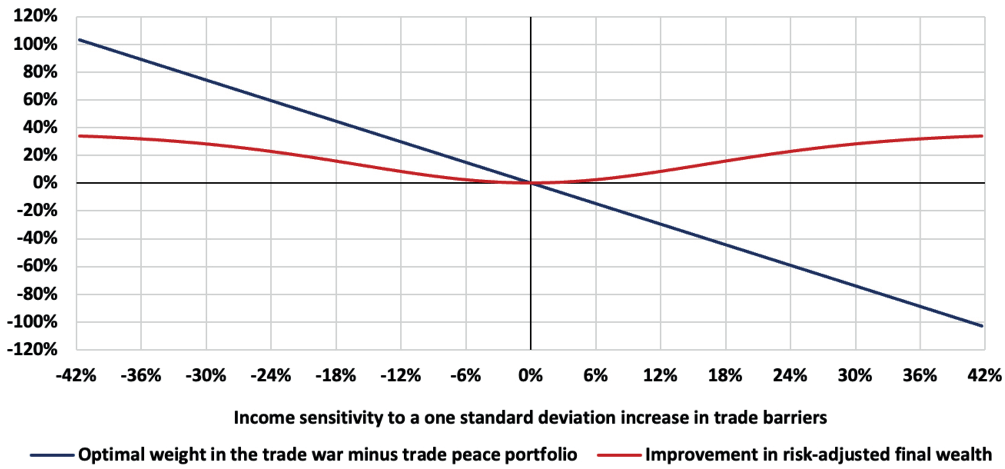
More interestingly, our illustration shows that the optimal deviation from the market portfolio due to trade policy exposures can be sizable. For example, an investor whose labour income decreases by 10% following the introduction of substantial tariffs should invest around 25% in the hedging portfolio. This means that around 25% of the weight in the market portfolio is sold to invest it elsewhere. While

28 - See also Davis and Willen (2014) for related work.

7. Applications

this is the outcome of a simple model and a particular set of parameters, it does show that the impact of hedging considerations on portfolio construction can be large. Analysing this question in depth would be an interesting topic for future research. For example, the simple model could be made more realistic by considering multiple periods with varying degrees of trade policy risk or labour income sensitivities, the negative aggregate effect of increases in trade barriers, or a potential cost of hedging trade policy risk. Moreover, where we simply describe results for a range of labour income sensitivities, these values could be calibrated based on specific occupations to make results more directly applicable in practice[29]. Other extensions and improvements to this stylised setting are no doubt possible, and our exposure measure can be used to implement these.

Exhibit 13: Portfolio choice with a trade war minus trade peace portfolio
The blue line in the graph shows the optimal allocation to a long-short trade war minus trade peace portfolio for investors whose labour income has different sensitivities to shocks in trade policy. The red line shows the percentage point improvement in risk-adjusted wealth due to this allocation, compared to the case when the long-short trade war minus trade peace portfolio was absent. Risk-adjusted wealth is defined as the ratio of expected wealth and the standard deviation of wealth. The x-axis represents the percentage change in an investor's labour income due to a one standard deviation increase in trade barriers. Details on the parameters and assumptions underlying these results are described in the appendix.



Reallocation Effects

While a large body of literature focusses on the aggregate effects of trade barriers, various papers also discuss how changes in trade policy have heterogeneous effects across sectors, thereby resulting in a reallocation of wealth, output, or employment, among others. For example, Fajgelbaum et al. (2020) find that the 2018 tariffs have a small aggregate effect on the US economy but substantial redistribution effects from buyers of foreign goods to US producers and the government. Also based on the trade policy changes in 2018, Charbonneau and Landry (2018) document considerable changes in trade flows and sectoral output reallocations, while confirming the modest impacts on long-run aggregate output levels. Furthermore, Caldara et al. (2020) find that firms more exposed to trade policy uncertainty invest less and therefore have a relatively lower capital stock after an increase in trade policy uncertainty. Bustos (2011) analyses tariff reductions between Argentina and Brazil in light of the Mercosur agreement and notes that firms increase their investments in technology faster

29 - Our definition of what a one standard deviation increase in trade barriers entails and the assumption that trade policy shifts follow a normal distribution could also be specified more accurately.

7. Applications

in industries where tariffs fall more. These investment effects point to a longer-term channel of trade policy changes on the structure of an economy and further highlight reallocation effects.

Our exposure measure can add value to this line of research because it consistently allows to distinguish between firms with positive or negative exposure to shifts in trade policy[30]. Furthermore, as opposed to Caldara et al. (2020) who capture exposure to trade policy uncertainty (i.e., a second moment effect) our measure aims to capture the direction of exposure (a first moment effect). It is therefore a useful complement to their measure.

We provide an illustration by combining our measure with the cumulative abnormal returns presented above in the ex-post validation analysis in section 3. For each of the seven events in Exhibit 4, we multiply each firm's market capitalisation at the last closing price before the event day with its estimated cumulative abnormal return around the event. Then, we take the sum of these products across all peace firms and across all war firms, defined based on the 70th and 30th percentile values of the combined exposure score. This gives us an idea of the total change in market capitalisation for both groups of firms due to the event and reflects market expectations regarding the impact of the tariff announcements. Across the seven events, trade peace firms on average lost USD55.0bn, while trade war firms on average gained USD50.3bn in market capitalisation. These values show a large reallocation of market value from trade peace firms towards trade war firms. Note that the cumulative abnormal returns provide a clean measure of reallocation effects since our definition of normal returns controls for aggregate market movements[31].

While this illustration quantifies the impact of the 2018-2019 tariff announcements in terms of market capitalisation, other variables and trade policy shifts could be used in a similar fashion. It would be interesting for further research to analyse the difference between trade peace and trade war firms in terms of investments, output, and employment, among others, around trade policy shifts. This could reveal the economic channels via which firms are affected by the change in policy and shed light on whether market reactions are justified. Furthermore, given that our measure is independent of specific events, this approach can be used to analyse the reallocation effects of a wide range of trade policy changes.

30 - In the case of concrete tariff announcement, where the impacted goods are clear, this exposure could be defined based on the sectors on which the tariffs will have a direct effect. However, this is not always feasible because not all trade policy actions target a clear set of goods. For example, after the Brexit vote the probability of new trade barriers between the UK and the EU increased without necessarily having clarity on which goods or services would be most impacted. Our measure has the advantage that it can be used to distinguish between firms for all types of shifts in trade policy and is independent of a specific event.
31 - One could make the case to use the cumulative abnormal returns themselves as the measure of exposure, as in Greenland et al. (2020). However, while abnormal returns are specified to isolate the return component driven by the trade event, these values inevitably include some unrelated price fluctuations. Such an approach would therefore overestimate the true impact. Defining firms as more positive and negative exposed based on an external variable, such as our exposure measure, is therefore preferred for this application.

8. Conclusion

8. Conclusion

Historically, there has been a long-term trend towards free international trade, but not without important reversals towards protectionism. Shifts in trade policy influence the structure of the economy, creating winners and losers. This paper proposes a multi-dimensional measure that captures firms' exposure to such shifts. We assess this measure of exposure via a double validation procedure using both stock returns and trade sentiment. As a result, we document substantial heterogeneity in the impact of trade policy shifts across firms.

Our exposure measure is based on firm characteristics used in previous research. It combines the information captured by the tradability of the goods produced by a firm, the share of the output in the firm's industry that is exported, and the attention given to trade policy in the firm's official risk disclosures. Furthermore, we also make use of stock market information when constructing the exposure measure. Each of the three characteristics is augmented with a covariance score that captures how similar a stock behaves compared to stocks with a high characteristic score. Adding covariances in the exposure measures allows us to extract information in stock returns that solely characteristics-based measures ignore. This multi-dimensional exposure measure also has the advantages that it is granular and available for all firms. Using a single characteristic to measure exposure would miss important information, since for many firms, characteristics are not available or are not able to discriminate between firms. Combining characteristics and extracting information from stock returns has the potential to lead to a more reliable measure of exposure.

We show that the exposure measure succeeds in capturing variation in exposure to shifts in trade policy out-of-sample via a double validation procedure that considers both price effects and sentiment. To assess price effects, we use abnormal returns around tariff announcements in the US-China trade war as an ex-post proxy of firms' exposures. Our results show that trade war stocks have positive stock price reactions to these announcements while trade peace stocks react negatively. We further show that each dimension contains relevant incremental information and that the combined measure captures all this information. Next to being statistically significant, these results are also economically significant. Trade war and trade peace stocks exhibit average return differences of 140bp over six trading days around the tariff announcements. Especially during periods of regular or large trade policy changes, these differences are important. In addition, we show that the multi-dimensional measure of exposure adds information beyond standard firm classifications and, beyond the US evidence, also captures return effects after trade policy shocks in international markets. To assess sentiment, we analyse discussions about trade policy during firms' quarterly earnings calls. Our multi-dimensional exposure measure is able to distinguish between firms with relatively positive and negative trade sentiment during a period of turbulent trade policy. The fact that we obtain supportive evidence for our measure based on both stock returns and sentiment during earnings calls strengthens our confidence that it reliably captures exposure to shifts in trade policy out-of-sample.

Overall, we find consistent evidence, both when analysing return effects and sentiment, that the multi-dimensional measure reliably captures heterogeneity across firms around trade policy shocks. The measure adds value to other approaches in the literature because it is granular, is available for

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all firms, combines the information from multiple data sources, captures exposures out-of-sample, and is independent of specific trade policy changes. These attributes ensure that it is useful for a wide range of potential applications. Among others, we illustrate that it can be used in asset pricing to test whether exposure to trade policy risk is rewarded, it allows to construct portfolios that hedge risk exposures in non-tradable sources of investors' overall wealth, and it can add value to research that analyses reallocation effects of shifts in trade policy.

Appendix

Appendix

Relationship between Import Share and Export Share

Our second characteristic, export share, measures a sector's realised sale of goods and services abroad. This is just one way in which sectors engage in international trade. Another way is by importing the necessary inputs for production from foreign countries. Some studies take into account both sides of a sector's participation in international trade. For example, De Gregorio, Giovannini, and Wolf (1994) and Lombardo and Ravenna (2014) calculate a sector's exposure to international trade as the sum of both its export share (the value of exports divided by the total value of output) and its import share (the value of imports divided by the total value of output). Others, like Tian (2018), only consider a sector's export share.

Notice that we are not interested in a precise estimate of the value of the participation in international trade because we use our sectors' characteristics only to rank stocks. Therefore, accounting for import share would significantly impact our results only if there was a considerable divergence between the sectors' ranks generated by import share and export share. In other words, import share would be redundant if it ranked sectors as export share. We confirm that import share is indeed redundant analysing its cross-sectional relationship with export share.

First, we calculate the import share for the 36 OECD sectors in a manner similar to that of the export share, but by replacing the sum of exports with the sum of imports as shown in the following equation.

$$Import\ share_s = \frac{\sum_c Imports_{s,c}}{\sum_c Output_{s,c}}$$

In the equation above, *s,c* indicates a sector-country pair and the sums are taken across all countries.

We then analyse the cross-sectional relationship of import share with the export share for the 36 OECD sectors over each year in our sample. We calculate both linear and rank cross-sectional correlation[32], but we highlight that our main interest is in the relationship between the rankings because we use our measures of exposure to rank stocks. We present the results in Exhibit 14. We find that the linear correlation between export share and import share is consistently above 0.9 for all the years in our sample, with an average of 0.92 over time. Rank correlation is even stronger, always above 0.97, and with an average of 0.98. This indicates that the rankings generated by export share and import share are almost identical, hence, accounting for import share would not add any distinctive information[33].

Exhibit 14: Cross-sectional correlation between export share and import share.
The table shows the linear (first row) and rank (second row) cross-sectional correlation between export share and import share of the 36 OECD sectors for each year from 2005 to 2015 and the time-series average of the measures of correlation in the last column. We compute linear correlation as simple correlation between the values of export share and import share. We compute rank correlation as Spearman's rank correlation between the values of export share and import share.

Type of Correlation	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Time-Series Average
Linear	0.94	0.92	0.92	0.91	0.91	0.92	0.91	0.91	0.91	0.92	0.93	0.92
Rank	0.99	0.99	0.98	0.99	0.98	0.98	0.98	0.99	0.98	0.97	0.97	0.98

32 - Rank correlation is Spearman's rank correlation.
33 - Please note that we are not suggesting that obtaining more detailed information about import sourcing is not valuable. More sophisticated information about imports could help to capture the different aspects of exposure to trade policy risk, and our risk disclosures measure may incorporate this information. The analysis in this section is specific to the import share measure obtained from the OECD input-output tables. Our findings indicate that incorporating this import share measure into our combined measure would not improve it since the relevant information is already captured by the export share measure.

Appendix

Details on the Risk Disclosures Characteristic

To obtain the risk disclosures characteristic, we start by collecting a set of clean and preprocessed risk disclosure texts for the stocks in our universe. We collect these from 10-K filings with a filing date between January 2006 and June 2019. The start date follows from the SEC's introduction of the requirement to include section 1A 'risk factors' for fiscal years ending after 1 December 2005. This text data is collected via the following steps.

- Map our universe to the SEC's Central Index Key (CIK) identifiers

We use the mapping provided online by the SEC to create a list of all the CIKs, the firm identifier the SEC uses in the EDGAR system, for which we want to collect risk disclosures. This mapping can be accessed via https://www.sec.gov/include/ticker.txt.

- Collect a list of 10-K filings per firm

For each of the relevant CIK identifiers, we then obtain a list of the corresponding 10-K filings via a Python script that accesses URLs of the following type.
https://www.sec.gov/cgi-bin/browse-edgar?action=getcompany&CIK=320193&type=10-K
The part of the URL indicating the CIK, in italics, is systematically replaced. These webpages provide a table with the history of 10-K filings of the relevant firm. We filter this table according to the abovementioned dates and remove any amendment filings. From this table, we obtain the accession number of each 10-K filing of interest, used in the next step.

- Collect the text of a 10-K filing

The text from a 10-K filing can be obtained via URLs of the following type.
https://www.sec.gov/Archives/edgar/data/320193/0001193125-08-224958.txt
Based on the list of CIKs with the corresponding 10-K filing accession numbers, both indicated in italics in the URL above, we can therefore obtain the text of all 10-K filings of interest. We parse this html code to obtain cleaned text of the 10-K filings in a regular format.

- Extract the risk disclosures section

From the full text of a 10-K filing, we extract section 1A 'risk factors' via a text-searching algorithm. We first split the text into parts defined by the word item, since new sections in a 10-K file are indicated with for example *Item 1. Business* or *Item 1A*. Risk factors. We then find all parts that start with *Item 1A. Risk factors* and append subsequent parts until one starts with *Item 1B. Unresolved*. If *Item 1B*. Unresolved is not found, the algorithm searches for *Item 2*. Properties instead. At this stage, it is possible that multiple candidates are found since *Item 1A. Risk factors* can also be referred to from other section in the filing. We select the shortest resulting text, conditional on it being longer than 2,000 characters, as the risk disclosures text. Allowing for shorter texts risks selecting a part of the table of contents or may indicate that there is no substantial content in the risk disclosures section. Longer texts tend to start at a point where *Item 1A. Risk factors* is referred to earlier in the filing. These rules are the result of iterative testing combined with manual checks. Results of one representative round of these checks are as follows. We manually inspected the outcome for a random sample of

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50 filings. For 48 of these filings, the algorithm correctly extracted the risk disclosures section. The remaining two files followed a non-standard format and consequently no risk disclosure text was extracted. These results reassure us that the process is reasonably accurate.

- Preprocess the risk disclosures text

The risk disclosure text is preprocessed using Python's NLTK package before the risk disclosure characteristic is calculated. We use the regular expression tokeniser to define a token as a group of alphanumeric characters, standard English stop words are removed, and we use the Snowball stemmer to transform each token into its root form. We confirmed that the removal of stop words does not have a material impact on the results in our paper. However, stemming does lead to some differences in results. We manually inspected a sample of risk disclosure text fragments containing terms that would not be counted as a trade keyword without stemming, e.g., *tariffs*. A large majority of these terms capture discussions on trade policy. Therefore, we decide to apply stemming.

Every June from 2006 until 2019, we calculate the risk disclosures characteristic measure for the stocks in our universe based on their most recent risk disclosures text available at that moment. If no risk disclosures less than five quarters old are available, the risk disclosure characteristic is considered missing. The measure is defined as the fraction of words in the preprocessed risk disclosures text that are in the trade dictionary shown in Exhibit 15. This dictionary is based on the trade-specific keywords proposed by Baker, Bloom, and Davis (2016) and Caldara et al. (2020). Note that these terms are also stemmed before calculating the measure.

Exhibit 15: Trade dictionary
The table shows the terms in our trade dictionary. These terms are based on the trade-specific keywords proposed by Baker, Bloom, and Davis (2016) and Caldara et al. (2020). The keyword tariff is excluded for firms in the telecom and utility sectors.

Trade dictionary	
tariff*	World Trade Organization
import duty	trade treaty
import barrier	trade agreement
import ban	trade policy
import tax	trade act
import subsidies	trade relationship
export ban	free trade
export tax	Doha round
export subsidies	Uruguay round
government subsidies	dumping
GATT	border tax
WTO	

Although the relationship between the augmented risk disclosures measure and abnormal returns around trade policy shifts documented in the paper indicates that we capture relevant information with our measure, we also conducted a manual audit exercise on the text fragments that are captured by the trade dictionary. An important sanity check when using text-based measures is to assess whether

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a human reader would confirm that the automatically detected text contains the information that we assume it does. Therefore, we manually read a random sample of 50 risk disclosures in which no trade terms were found and all text fragments containing trade terms from a second random sample of 50 risk disclosures containing at least one trade term. In the first sample, we find that 38 out of 50 risk disclosures indeed do not mention any risks related to international trade policy. Therefore, it seems that we do a reasonable job in terms of recall. Although some relevant discussions are not captured, we decide against expanding our externally obtained dictionary based on the sample data given our concern for out-of-sample robustness of the proposed exposure measure. The fragments containing trade terms in 46 out of 50 risk disclosures in the second sample correctly capture discussions related to international trade policy. The trade dictionary therefore scores well in terms of precision. This manual audit also supports our interpretation that trade terms are mostly mentioned to indicate that a firm would suffer from an increase in trade barriers.

The keyword *tariff* represents around two thirds of the number of mentions of trade terms in our sample of risk disclosures. Given its importance, we did some further checks specifically focussed on this term. While our manual audit described above indicates that *tariff* accurately captures discussions related to international trade policy in general, we did notice that the term is also often used in another context in certain industries. Therefore, we obtained an additional random sample of 30 risk disclosures mentioning at least one term in the trade dictionary, only from firms in the utilities sector. Some 28 out of these 30 risk disclosures mention *tariff* in the context of regulated prices, instead of in an international trade policy context. We carried out a similar exercise for firms in the telecoms sector, although only 15 telecom firms in our sample mention any trade dictionary terms in their disclosures. Still, one third of these firms also used *tariff* in the context of consumer prices. Consequently, we decided to omit *tariff* from the trade dictionary when calculating the risk disclosures characteristic for firms in the telecoms and utilities sectors to improve the accuracy of the text captured.

Several methods are proposed in the literature to extract information from text data, see Gentzkow, Kelly, and Taddy (2019) or Loughran and McDonald (2016, 2020) for an overview. Following the discussion in Gentzkow, Kelly, and Taddy (2019), we use a dictionary-based method. Supervised models are not feasible in our setting since no obvious labelled training data is available and trade policy discussions will at best be only a relatively small part of the full risk disclosures text, so unsupervised models such as topic models are unlikely to pick up trade policy as a topic. Furthermore, we can rely on the extensive work done by Baker, Bloom, and Davis (2016) and Caldara et al. (2020) to construct an expert-curated dictionary that is relevant in a financial context. We therefore consider that prior information regarding the relevant trade terms is strong in our case.

Within the area of dictionary-based approaches, more automated methods to obtain a relevant dictionary, compared to using an expert-curated dictionary, are also proposed. We have tested the methodology of Hassan et al. (2019), who construct a thematic dictionary based on a set of reference documents. First, all bigrams are taken from a document or set of documents considered archetypal

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for the theme of interest and given a weight according to how often they occur in these documents. Then, bigrams that occur in a set of control documents are filtered out to avoid including general language terms in the dictionary. This results in a thematic dictionary of bigrams in which each bigram receives a weight to indicate its relevance to the theme. The key degree of freedom in this approach is the definition of the reference and control documents. We tested several specifications, including a textbook on international trade or publications from the United Nations Conference on Trade and Development as reference documents and a risk management or general business management textbook as control documents. Manual audits similar as the one described above, however, indicated that this methodology lacks precision in our setting. Several influential terms, which have a high weight and occur often in the risk disclosures, were mostly used in the wrong context. We therefore did not explore the use of this methodology further and decided to focus on the expert-curated dictionary presented in Exhibit 15.

Information Captured by the Three Dimensions

Exhibits 16-18 give an indication of the information captured by each of the three dimensions via some concrete examples. Exhibit 16 shows the five industries with the highest and lowest tradability characteristic, together with the largest firm in our universe in this industry. Exhibit 17 shows similar information based on the export share characteristic. Exhibit 18 presents risk disclosure text fragments that are captured by the risk disclosures characteristic. These examples are all based on the most recent observations in our dataset, corresponding to the values used to obtain exposure scores in June 2019.

The results in Exhibit 16 are intuitive. Goods that require specialised knowledge to create, such as spacecraft machinery or pharmaceuticals, are highly tradable. Shipping costs, which is expressed relative to the value of the goods, are relatively low for these products because they are valuable. On the other side of the spectrum, we find cement, stone, and sand. Clearly, these are goods that can be produced nearly everywhere and are very heavy compared to their value, which makes them expensive to transport. It makes economic sense that producers of these goods will be less involved in international trade than the firms producing highly tradable goods. Consequently, an increase in trade barriers should hurt the latter relatively more.

Exhibit 17 shows that many of the industries with the highest export share are the same ones as those with the highest tradability. Manufacturers of electromedical and electrotherapeutic equipment, computers, or communication equipment show up in both tables. Presumable due to the high tradability of the goods they produce, firms in these industries export a relatively large fraction of their output. However, the industries with the lowest export share highlight why this characteristic adds incremental information over tradability. Several of these industries are service industries, which tradability cannot capture. Again, the results are intuitive. Child day-care, nursing care, and other human health activities are inherently domestic services. Likewise, it does not seem surprising that construction or electrical installation companies operate mostly locally.

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Lastly, Exhibit 18 shows the text that is captured by the risk disclosures characteristic. We selected risk disclosure fragments that contain terms in our trade dictionary from the five largest firms in our universe, as of June 2019, that mention at least one dictionary term in their most recent disclosures. Note that these are not necessarily the only paragraphs in which relevant terms were mentioned, but we selected the ones that seemed most relevant. All these fragments indicate that an increase in trade barriers, often specifically *tariffs*, would have a negative effect on the firm. This supports the way we define and use the risk disclosures measure.

Exhibit 16: Industries with the highest and lowest tradability characteristic
The table reports the five industries with the highest and lowest tradability characteristic together with the largest firm in our universe in each of those industries. The industry selection is based on shipping cost data from 2018 and the NACE industry classification. Firm size is based on market capitalisation in June 2019. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Industry	Example firm
Highest tradability	
Manufacture of air and spacecraft and related machinery	The Boeing Company
Manufacture of irradiation, electromedical and electrotherapeutic equipment	Medtronic plc
Manufacture of pharmaceuticals, medicinal chemical and botanical products	Johnson & Johnson
Manufacture of computers and peripheral equipment	NVIDIA Corporation
Manufacture of communication equipment	Apple Inc.
Lowest tradability	
Manufacture of cement, lime and plaster	Eagle Materials Inc.
Manufacture of soft drinks; production of mineral waters and other bottled waters	The Coca-Cola Company
Mining of chemical and fertiliser minerals	Compass Minerals International, Inc.
Quarrying stone, chalk and slate	Vulcan Materials Company
Operation of gravel and sand pits; mining of clay minerals	U.S. Silica Holdings, Inc.

Exhibit 17: Industries with the highest and lowest export share characteristic
The table reports the five industries with the highest and lowest export share characteristic together with the largest firm in our universe in each of those industries. The industry selection is based on export and output data from 2018 and the NACE industry classification. Firm size is based on market capitalisation in June 2019. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq

Industry	Example firm
Highest export share	
Manufacture of electronic components	Intel Corporation
Manufacture of instruments and appliances for measuring, testing and navigation	Danaher Corporation
Manufacture of communication equipment	Apple Inc.
Manufacture of irradiation, electromedical and electrotherapeutic equipment	Medtronic plc
Manufacture of computers and peripheral equipment	NVIDIA Corporation
Lowest export share	
Construction of residential and non-residential buildings	D.R. Horton, Inc.
Electrical installation	Quanta Services, Inc.
Residential nursing care activities	Acadia Healthcare Company, Inc.
Other human health activities	Laboratory Corporation of America Holdings
Child day-care activities	Bright Horizons Family Solutions Inc.

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Exhibit 18: Text fragments captured by the risk disclosures characteristic
The table reports text fragments from 10-K risk disclosures that are captured by the risk disclosures characteristic for the five largest firms in our universe that mention at least one of the terms in our trade dictionary. Firm size is based on market capitalisation in June 2019. We manually selected relevant fragments that contain trade dictionary terms from the most recent 10-K filings before June 2019. Terms in our trade dictionary are indicated in bold. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Firm	Risk disclosure fragment
Apple Inc. 10-K filing for the fiscal year ending 29 September 2018	International trade disputes could result in **tariffs** and other protectionist measures that could adversely affect the Company's business. **Tariffs** could increase the cost of the Company's products and the components and raw materials [...]. **Tariffs** could also make the Company's products more expensive for customers [...]. Countries may also adopt other protectionist measures that could limit the Company's ability to offer its products and services.
JPMorgan Chase & Co. 10-K filing for the fiscal year ending 31 December 2018	Furthermore, governments in particular countries or regions in which JPMorgan Chase or its clients do business may choose to adopt protectionist economic or **trade policies** [...]. Any or all of these developments could lead to diminished cross-border trade and financing activity within that country or region, all of which could negatively affect JPMorgan Chase's business and earnings in those jurisdictions and increase its operational costs.
Alphabet Inc. 10-K filing for the fiscal year ending 31 December 2018	Our international operations expose us to other risks, including the following: [...] Import and export requirements, **tariffs**, trade disputes and barriers, and customs classifications that may prevent us from offering products or providing services to a particular market and may increase our operating costs.
Microsoft Corporation 10-K filing for the fiscal year ending 30 June 2018	Emerging nationalist trends in specific countries may significantly alter the trade environment. Changes to **trade policy** or agreements as a result of populism, protectionism, or economic nationalism may result in higher **tariffs**, local sourcing initiatives, or other developments that make it more difficult to sell our products in foreign countries.
Amazon.com, Inc. 10-K filing for the fiscal year ending 31 December 2018	In addition to risks described elsewhere in this section, our international sales and operations are subject to a number of risks, including: [...] restrictive governmental actions (such as trade protection measures, including export duties and quotas and custom duties and **tariffs**)

Out-of-Sample Robustness of the Covariance Scores

Augmented scores for each of the risk disclosures, export share, and tradability dimensions are obtained by combining the original characteristic scores with a covariance score. As described in the paper, covariance scores are estimated based on a regression of a stock's excess returns on the returns of a mimicking portfolio. The latter captures the difference in return between stocks with a high characteristic score and stocks with a low characteristic score. Therefore, covariance scores capture whether a stock's returns behave similar as the returns of stocks with a high characteristic score. Importantly, these covariances are estimated based on past data at each point in time. One could therefore question whether the covariance scores contain useful information to capture exposure to shifts in trade policy out-of-sample, or whether they just add noise to the information in the characteristic scores. Since our final aim is to obtain exposure scores that are useful out-of-sample, the covariance scores should also capture the comovement of a stock's returns with returns of stocks with a high characteristic score out-of-sample.

To test this, we create a long-short portfolio that equally weights the 20% of firms with the highest covariance score in the long leg, and equally weights the 20% of firms with the lowest covariance score in the short leg. This portfolio is rebalanced annually in June, using the covariance scores that are estimated based on past data at each rebalancing date. Then, we regress this long-short portfolio on the corresponding mimicking portfolio that was used to estimate the covariance scores, while controlling for the market factor. A significantly positive coefficient would indicate that the returns of stocks with a high covariance score still behave similar as the returns of stocks with a high characteristic

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score out-of-sample. Since we obtain covariance scores for every June from 2008 until 2019, these regressions are based on data from end of June 2008 until December 2019.

Exhibit 19 shows the results of this analysis for each of the risk disclosures, export share, and tradability dimensions. In all three cases, the coefficient for the mimicking portfolio is significantly positive. The covariance scores are therefore robust out-of-sample. Moreover, the adjusted R-squared values of these regressions are between 47.5% for tradability and 81.7% for export share. This indicates that variation in the returns of the long-short portfolio based on covariance scores is largely explained by the mimicking portfolio returns[34].

Exhibit 19: Out-of-sample robustness of covariances
The table shows the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of the returns of a long-short portfolio based on the covariance scores on the returns of the market factor and the returns of the mimicking portfolio used to obtain the covariance scores. Column headers indicate whether the dependent variable and the mimicking portfolio are based on the risk disclosures, export share, or tradability dimension. Stocks with a score higher than or equal to the 80th percentile are selected in the long leg and stocks with a score lower than the 20th percentile are selected in the short leg of the dependent variable, and both legs are equally weighted and rebalanced annually in June. The returns on the market factor are returns on a cap-weighted portfolio of all stocks in the universe in excess of the risk-free rate. The results are based on daily returns from 30 June 2008 until 31 December 2019. The t-statistics are adjusted for heteroskedasticity and autocorrelation. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Out-of-sample robustness of covariances	Risk Disclosures	Export share	Tradability
Intercept	-0.01%	-0.02%	0.02%
	(-1.0)	(-2.3)	(1.4)
Market factor	0.1	0.1	-0.2
	(6.4)	(4.3)	(-9.1)
Mimicking portfolio	**2.6**	**1.5**	**0.8**
	(55.6)	**(66.2)**	**(22.5)**
Adj. R-squared	72.6%	81.7%	47.5%

Relation between Covariance Scores and Cumulative Abnormal Returns

Throughout the paper, we test whether the augmented tradability, export share, risk disclosure, and combined measures capture exposure to shifts in trade policy. These measures combine the information in both characteristics and covariances. Since we are interested in how a stock reacts to a change in trade policy, using only the returns-based covariance scores may also seem reasonable. We decided to combine covariances with characteristics as an additional form of shrinkage because the estimation of the covariances adds an extra layer of estimation risk. Nonetheless, the use of covariances alone leads to similar conclusions.

Exhibit 20 presents results similar to those in Exhibit 6 in the paper but is based on covariances instead of the augmented scores. Therefore, it shows the results of cross-sectional regressions with the cumulative abnormal returns as dependent variable, and the covariance measures as independent variables. All other specifications are identical to those used to obtain the results in Exhibit 6. Observations are pooled across the seven event dates, cumulative abnormal returns are de-meaned per event, covariance scores as of the most recent June before each event date are used and standardised to a z-score per event.

34 - In unreported results, we confirmed that omitting the market factor only has a minor impact on the adjusted R-squared values.

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The results show that our conclusions in the paper are robust to the use of covariances alone. Each of the tradability, export share, and risk disclosures covariance score has a significantly negative relation with the cumulative abnormal returns. Furthermore, the fourth column shows that this negative relationship persists once we control for the information in the other two dimensions. The main difference compared to using the augmented scores is that the results for tradability and export share in the fourth column are not statistically significant at conventional levels, with t-statistics of -1.6. Therefore, we argue that the additional shrinkage introduced by combining covariances with characteristics may be useful to accurately capture exposures to shifts in trade policy.

Exhibit 20: Relation between covariance scores and cumulative abnormal returns
The table reports the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of cumulative abnormal returns on tradability, export share, and risk disclosures covariance scores. Cumulative abnormal returns are based on the CAPM model to estimate normal returns and an event window from the event day until one week after the event. The event dates are 01/03/2018, 22/03/2018, 02/04/2018, 15/06/2018, 17/09/2018, 10/05/2019 and 23/08/2019. Values for the independent variables as of the most recent June before each event are used. All event dates are pooled together in the regression, with cumulative abnormal returns de-meaned per event and regressors transformed to a z-score per event. The t-statistics are adjusted for heteroskedasticity. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Relation between covariance scores and cumulative abnormal returns	(1)	(2)	(3)	(4)
Tradability	-0.3%			-0.2%
	(-2.1)			(-1.6)
Export share		-0.5%		-0.2%
		(-6.2)		(-1.6)
Risk disclosures			-0.7%	-0.4%
			(-11.6)	(-3.5)
Adj. R-squared	0.5%	1.2%	2.5%	2.6%

Alternative Specifications for Cumulative Abnormal Returns

Throughout the paper, we rely on our estimates of cumulative abnormal returns as an ex-post proxy for exposure to shifts in trade policy. These estimates require us to specify a model for normal returns and the length of the event window during which we expect the event to influence share prices. While our choices are standard, other reasonable choices could be made. However, we will show that our results are not sensitive to such alternative specifications. More precisely, we obtain three alternative version of the cumulative abnormal returns. First, we use the Fama-French (2015) five-factor model instead of the CAPM to estimate each stock's normal returns during the standard one-week event window. Second, we define a shorter event window as the event day and the subsequent day. Third, we define a longer event window as the event day together with the subsequent two weeks. In the latter two cases, we use the CAPM model for normal returns to be able to analyse one specification change at a time.

Exhibit 21 shows results for the same set of regressions as presented in Exhibit 6, but using the alternative versions of the cumulative abnormal returns as the dependent variable. The results in Panel A show the impact of changing the model for normal returns. These results are almost identical to those based on our main specifications. Therefore, our main results are not influenced by systematic

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differences in exposures to the Size, Value, Profitability, and Investment factors between trade war and trade peace firms.

Exhibit 21: Relation between exposure scores and cumulative abnormal returns - Alternative specifications
The table reports the coefficients, t-statistics (in brackets) and adjusted r-squared values of regressions of cumulative abnormal returns on augmented tradability, augmented export share, augmented risk disclosures, and/or combined scores. Cumulative abnormal returns are based on the CAPM model to estimate normal returns in panels B and C and the Fama-French 5-factor model in panel A. The event windows are from the event day until one week after the event in panel A, until one day after the event in panel B, and until two weeks after the event in panel C. The event dates are 01/03/2018, 22/03/2018, 02/04/2018, 15/06/2018, 17/09/2018, 10/05/2019 and 23/08/2019. Values for the independent variables as of the most recent June before each event are used. All event dates are pooled together in the regression, with cumulative abnormal returns de-meaned per event and regressors transformed to a z-score per event. The t-statistics are adjusted for heteroskedasticity. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Relation between exposure scores and cumulative abnormal returns - Alternative specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Fama-French five-factor model for normal returns								
Tradability	-0.3%			-0.3%		0.0%		
	(-6.1)			(-4.9)		(0.3)		
Export share		-0.5%		-0.3%			0.0%	
		(-12.0)		(-3.9)			(0.1)	
Risk disclosures			-0.5%	-0.3%				-0.1%
			(-11.9)	(-4.4)				(-0.7)
Combined					-0.6%	-0.6%	-0.6%	-0.6%
					(-14.2)	(-14.2)	(-5.9)	(-7.2)
Adj. R-squared	0.7%	1.4%	1.8%	2.3%	2.3%	2.3%	2.3%	2.3%
Panel B: two-day event window								
Tradability	-0.1%			-0.1%		0.0%		
	(-3.1)			(-2.4)		(-0.6)		
Export share		-0.1%		0.0%			0.1%	
		(-3.2)		(-0.3)			(1.3)	
Risk disclosures			-0.1%	-0.1%				0.0%
			(-5.1)	(-2.5)				(-0.6)
Combined					-0.1%	-0.1%	-0.2%	-0.1%
					(-5.9)	(-4.7)	(-3.5)	(-2.3)
Adj. R-squared	0.2%	0.1%	0.3%	0.4%	0.4%	0.4%	0.5%	0.4%
Panel C: two-week event window								
Tradability	-0.5%			-0.4%		0.0%		
	(-6.8)			(-5.5)		(-0.2)		
Export share		-0.7%		-0.4%			0.0%	
		(-11.4)		(-4.1)			(0.2)	
Risk disclosures			-0.7%	-0.4%				0.0%
			(-11.7)	(-4.1)				(-0.1)
Combined					-0.8%	-0.8%	-0.9%	-0.8%
					(-14.3)	(-13.3)	(-6.5)	(-7.4)
Adj. R-squared	0.9%	1.6%	1.9%	2.7%	2.7%	2.7%	2.7%	2.7%

Appendix

Panel B shows the results when using a shorter event window. As expected, the regression coefficients are lower in absolute value compared to the ones in Exhibit 6. This is due to the fact that the cumulative abnormal returns are calculated over less days. The lower values for the adjusted R-squared also indicate that the shorter event window results in more noise in the cumulative abnormal returns. Nonetheless, the main conclusions hold. All individual dimensions have a significantly negative relation with the cumulative abnormal returns in univariate regressions, the combined score captures all this information and consequently also has a significantly negative coefficient, and none of the individual dimensions add any value when controlling for the combined score. One difference is that the export share coefficient becomes insignificant when controlling for the other two dimensions, with a t-statistic of -0.3. However, this does not change the overall picture.

The results based on a two-week event window, shown in Panel C, are again very similar to our main results. Because of the additional days included in the cumulative abnormal returns, the absolute value of the coefficients and the adjusted R-squared values are now larger than in Exhibit 6. Otherwise, all observations from the table stay the same. The individual dimensions and the combined score have significantly negative coefficients in univariate regressions, and each dimension's coefficient stays significant when controlling for the other two but becomes insignificant when controlling for the combined score.

Comparing panels B and C together with the main results, we note that the regression coefficient for the combined score in column 5 increases in absolute value from -0.1% to -0.6% and -0.8% for two-day, one-week, and two-week event windows, respectively. This indicates that the tariff announcements impact the return of trade war and trade peace stocks, as captured by the combined score, differently both directly after the announcement and in the remainder of the two following weeks. Therefore, it seems that the market incorporates this news gradually in stock prices. In any case, Exhibit 21 shows that the combined exposure score is a useful measure to capture exposure to shifts in trade policy, regardless of how we specify the model for normal returns or the length of the event window when defining the ex-post proxy.

Exposure to Trade Policy Shifts per Sector

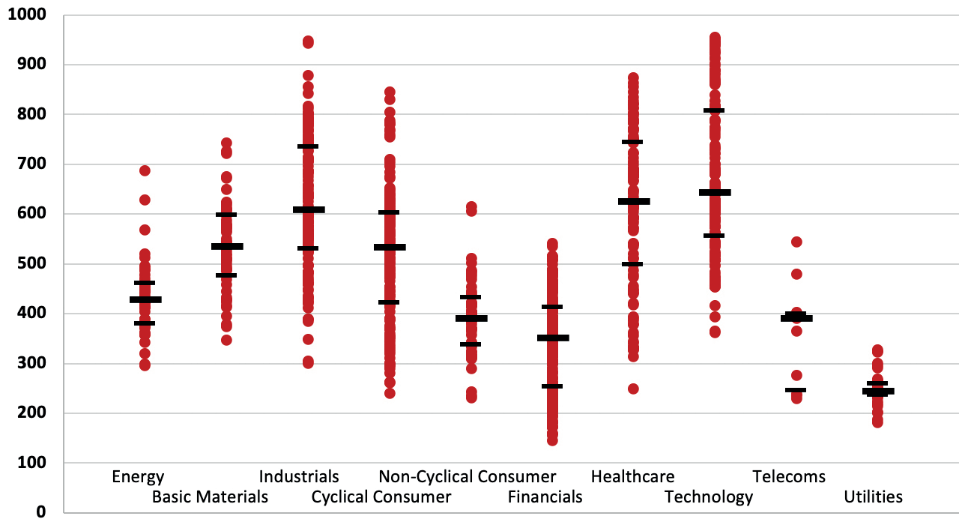
Exhibit 22 shows a scatter plot of all the firm-level combined exposure scores categorised per broad sector. The 25th, 50th, and 75th percentile values per sector are also indicated. The graph is based on data as of June 2019, i.e., the most recent available data in our sample.

There are clear differences across sectors in exposures to shifts in trade policy, as captured by our exposure score. Utilities and financial firms tend to be trade war firms that are relatively protected from increases in trade tensions, which makes intuitive sense given the domestic nature of their business. Technology, industrial, and healthcare firms, on the other hand, are more often classified as trade peace firms and are therefore more likely to suffer from increasing trade barriers. Nonetheless, the graph also indicates that much of the dispersion in the combined exposure score is not captured by

Appendix

this type of broad sector classifications. For example, around 25% of firms in the healthcare sector have a combined score below 500, with the lowest score being 250. This means that, although many healthcare firms tend to be trade peace firms, the sector also contains a sizable fraction of trade war firms. We can imagine that within such broad sectors, containing both pharmaceutical companies and hospitals, it is indeed accurate to consider that trade policy risk exposures vary strongly. This makes the results in Exhibit 7 in the paper, showing that our combined exposure score is preferred over sector classifications to capture dispersion in abnormal returns around trade policy shifts, unsurprising.

Exhibit 22: Combined exposure scores per sector
The graph shows the combined exposure scores for all stocks in the universe categorised per broad sector. The y-axis shows the value of the combined score and the different sectors are spread out over the x-axis. Each dot represents a firm and the 25th, 50th, and 75th percentile values per sector are indicated with the short lines. The sectors are defined based on Refinitiv's top-level TRBC classification. The analysis is based on data from June 2019. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.



Details on Trade Sentiment

We estimate a firm's trade sentiment as an ex-post proxy for exposure to shifts in trade policy. Trade sentiment is estimated from the text in earnings call transcripts, using a dictionary-based approach. The methodology is similar as the one used to construct the risk disclosures characteristic, with some notable differences.

Importantly, we use a different data source, earnings call transcripts. Usually, an earnings call consists of two parts. It starts with a presentation of the firm's management in which they discuss the results of the previous quarter and their outlook for the current and future periods. Then, it contains a Q&A section in which external analysts can ask questions to the management. Where risk disclosures are intended to cover an exhaustive list of material risk factors that may affect a firm in the future, earnings calls are more focussed on the factors that currently drive firm performance. This makes earnings calls a more suitable data source to capture the sentiment surrounding current shifts in trade policy, while risk disclosures are better suited to capture forward looking exposures to risks that not necessarily play an important contemporaneous role.

Appendix

We collect all available quarterly earnings call transcripts for the firms in our universe from Refinitiv. Header info, containing for example a list of call participants, indications of the start of the Q&A section, and speaker indications are removed to only retain text representing the actual spoken content. We then apply the same preprocessing steps to the resulting text as for the risk disclosures, i.e., tokenisation, the removal of stop words, and stemming.

From the preprocessed transcript text, we extract trade sentiment following Hassan et al. (2019). We first identify discussions related to international trade policy using the same dictionary as for the risk disclosures characteristic, shown in Exhibit 15. Trade policy discussions are defined as the text from 10 words before a trade term until 10 words after the term. Then, the methodology necessarily deviates from the one used for the risk disclosures characteristic to account for the different nature of the data source. Risk disclosures are very structured and per definition only discuss risks for a firm. Earnings calls are much less structured and can discuss both positive and negative consequences of international trade policy, or just factually discuss current events. Therefore, we need to capture whether trade policy discussions have a positive or negative connotation to understand the direction of the exposure. This is done using the positive and negative sentiment word lists from Loughran and McDonald (2011)[35]. Trade sentiment is defined as the difference between the number of positive and negative sentiment words in trade policy discussions, scaled by the total number of words in the transcript. To account for the fact that the word *question* often occurs with a neutral connotation in the Q&A portion of a transcript, we remove all words with the stem *question* from the negative sentiment word list.

As was the case in risk disclosures, the keyword *tariff* is by far the most commonly found term. It accounts for around 75% of all trade terms mentioned across the earnings call transcripts. Therefore, we pay extra attention to the accuracy of this term. Following Caldara et al. (2020), we do not count *tariff* as a trade term when it occurs adjacent to *feed-in, MTA, network, transportation, adjustment, regulate, rate,* or *escalator*. Our manual checks indicate that in these cases *tariff* is indeed likely used in a context not related to international trade. Also, as done when calculating the risk disclosures characteristic, we exclude *tariff* from the trade dictionary for firms in the utilities and telecoms sectors. Again, our manual validation checks indicate that this term is mostly used in the wrong context for firms in these sectors.

Manually inspecting two groups of 30 earnings calls, with a particularly high or low sentiment in the second half of 2018, confirms that *tariff* is the dominant keyword in these discussions. The fragments in all 60 of these earnings calls that are captured by the trade terms indeed discuss international trade policy, indicating that the trade dictionary is reasonably accurate in the period of interest[36]. Furthermore, the sentiment score corresponds to human interpretation of the underlying sentiment in around two thirds of the transcripts. This indicates that the trade sentiment score is broadly able to distinguish between a positive and negative connotation, but that some level of noise exists.

35 - These lists are obtained via https://sraf.nd.edu/loughranmcdonald-master-dictionary/. We thank the authors to make these dictionaries available.
36 - Manual checks on a random sample taken from across our entire sample period reveals an accuracy of around two thirds, indicating that the trade sentiment measure may contain more noise outside of the period of peaking trade policy attention, on which we focus in our analysis.

Appendix

We also tested the use of an alternative trade dictionary to construct the trade sentiment score, using the methodology proposed by Li et al. (2021). To construct this alternative dictionary, we first train a word embeddings model using the Gensim package in Python to obtain vector representations of the words in our text data. Then, we select relevant terms from the list of 100 terms whose vector is closest to the vectors for the seed terms *anti-dumping, embargo, retaliatory tariff, trade tension,* and *trade war*. For more details on the procedure, see Li et al. (2021). The resulting dictionary is presented in Exhibit 23. This alternative dictionary is more focussed on terms describing trade barriers, as opposed to the terms in our main expert-curated dictionary that tend to capture international trade more generally. We confirmed that our main conclusions are robust to the use of this alternative dictionary.

Exhibit 23: Trade dictionary obtained via word embeddings
The table shows the terms in an alternative trade dictionary, obtained following the methodology proposed by Li et al. (2021).

Trade dictionary obtained via word embeddings	
anti dumping	tariff
antidumping	trade barrier
countervailing duty	trade conflict
embargo	trade dispute
escalate trade	trade friction
export restriction	trade tension
import duty	trade war
nontariff	unresolved trade

Unconditional Performance of Trade War and Trade Peace Strategies

The goal of our paper is to propose a firm-level measure of exposure to shifts in trade policy. In section 7, we indicate that such a measure can be useful for testing whether trade policy risk or specific aspects of it are priced. The corresponding results shown in Exhibit 12 are based on long-short factor portfolios and only focus on returns or alphas. For completeness, we also report more general performance statistics of the long and short legs of the factor based on the combined exposure score separately in Exhibit 24. Hence, these results are based on cap-weighed portfolios that select the 30% of firms with either the lowest or highest exposure score for the trade war and trade peace strategies, respectively. The portfolios are rebalanced annually in June and results are based on returns from the end of June 2008 until December 2019. Since we only have data for a little over a decade, we caution against strong conclusions regarding long-term performance for the trade war and trade peace strategies. The performance of both strategies is relatively similar and close to the market performance in our sample. The annualised returns for the trade war and trade peace strategies are 8.8% and 11.2%, respectively. The corresponding Sharpe ratios are 0.4 and 0.5. Note also that the results in Exhibit 12 indicate that the return difference between both portfolios is not statistically significant.

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Exhibit 24: Unconditional performance of trade peace and trade war strategies
The table shows absolute and relative performance measures of strategies constructed based on the combined exposure score. The trade war strategy is a cap-weighted portfolio composed of all stocks with a combined score below or equal to the 30th percentile. The trade peace strategy is a cap-weighted portfolio composed of all stocks with a combined score above or equal to the 70th percentile. The broad market is a cap-weighted portfolio containing all stocks in the universe. The strategies are rebalanced annually in June. The analytics are based on daily returns from 30 June 2008 until 31 December 2019 and annualised, apart from the drawdowns. The universe consists of the 1,000 largest US firms traded on the New York Stock Exchange or Nasdaq.

Unconditional performance of trade peace and trade war strategies	Broad market	Trade war strategy	Trade peace strategy
Return	10.5%	8.8%	11.2%
Volatility	19.7%	21.2%	20.6%
Sharpe ratio	0.5	0.4	0.5
Max drawdown	47.7%	48.8%	48.8%
Relative return	-	-1.7%	0.7%
Tracking error	-	6.9%	4.8%
Information ratio	-	-	0.2
Max relative drawdown	-	27.1%	12.4%

Details of the Portfolio Choice Illustration

The results in Exhibit 13 are based on the assumptions and parameters described here. We consider a one-period setting in which an investor maximises his expected utility from final wealth. We assume an exponential utility function, where $\widetilde{W}$ represents the final wealth and A is the investor's absolute risk aversion.

$$U(\widetilde{W}) = -e^{-A\widetilde{W}}$$

Wealth consists of both financial and human capital. Final wealth $\widetilde{W}$ is the sum of the value of an equity portfolio $\tilde{P}$, and the accumulation of labour income during the period $\tilde{Y}$.

$$\widetilde{W} = \tilde{P} + \tilde{Y}$$

The equity portfolio consists of the equity market portfolio, which we will refer to as the market, and a dollar-neutral trade war minus trade peace portfolio, which we will refer to as the WMP portfolio. The investor is assumed to be 100% invested in the market and has to decide the weight θ in the WMP portfolio, i.e., how much to deviate from the market. At the end of the period, the value of the equity portfolio $\tilde{P}$ is therefore defined as follows, with P_0 representing initial financial wealth, $\widetilde{R_M}$ the return on the market, and $\widetilde{R_{WMP}}$ the return on the WMP portfolio.

$$\tilde{P} = P_0\left(1 + \widetilde{R_M} + \theta\widetilde{R_{WMP}}\right)$$

We assume that labour income and the returns on the WMP portfolio are affected by a common shock in trade policy $\tilde{T}$, but that market returns are unrelated to $\tilde{T}$. A positive shock $\tilde{T}$ is interpreted as an increase in trade barriers and a negative shock in $\tilde{T}$ as a decrease in trade barriers. Both labour income, market returns and WMP portfolio returns also depend residual sources of uncertainty ε. Lastly, we assume that the expected return on the WMP portfolio is zero, in line with the results in Exhibit 12.

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$$\widetilde{R_M} = \overline{R_M} + \varepsilon_M$$

$$\widetilde{R_{WMP}} = \beta_{WMP}\tilde{T} + \varepsilon_{WMP}$$

$$\tilde{Y} = \bar{Y} + \beta_Y\tilde{T} + \varepsilon_Y$$

Therefore, there are four sources of uncertainty in this model: $\tilde{T}$, ε_M, ε_{WMP}, and ε_Y. We assume that they are mutually independent and normally distributed with a mean of 0 and a variance of σ_T^2, $\sigma_{\varepsilon M}^2$, $\sigma_{\varepsilon WMP}^2$, and $\sigma_{\varepsilon Y}^2$, respectively. Consequently, the following holds.

$$Var(\tilde{P}) = \sigma_P^2 = P_0^2\left[\sigma_{\varepsilon M}^2 + \theta^2\left(\sigma_{\varepsilon WMP}^2 + \beta_{WMP}^2\sigma_T^2\right)\right]$$

$$Var(\tilde{Y}) = \sigma_Y^2 = \beta_Y^2\sigma_T^2 + \sigma_{\varepsilon_Y}^2$$

$$Cov(\tilde{P},\tilde{Y}) = \sigma_{P,Y} = P_0\theta\beta_{WMP}\beta_Y\sigma_T^2$$

The distribution of final wealth $\tilde{W}$ can then be expressed as follows, with $\bar{P} = P_0(1 + \overline{R_M})$.

$$\tilde{W} \sim N(\bar{W}, \sigma_W^2) = N\left(\bar{P} + \bar{Y}, \sigma_P^2 + \sigma_Y^2 + 2\sigma_{P,Y}\right)$$

Using the fact that $E[e^{-a\varepsilon}] = e^{-a\mu + \frac{1}{2}a^2\sigma^2}$ for $\varepsilon \sim N(\mu, \sigma^2)$, we can obtain the following expression for the investor's expected utility.

$$E\left[U(\tilde{W})\right] = -e^{-A\bar{W} + \frac{1}{2}A^2\sigma_W^2}$$

Maximising expected utility with respect to the weight in the WMP portfolio θ leads to the following expression for the optimal weight θ*.

$$\theta^* = \frac{1}{P_0}\left(\frac{-\beta_{WMP}\beta_Y\sigma_T^2}{\beta_{WMP}^2\sigma_T^2 + \sigma_{\varepsilon WMP}^2}\right)$$

To compute these optimal weights θ*, we consider the one period in our model as one year. We set initial financial wealth P_0=USD100,000, and expected labour income $\bar{Y}$ =USD60,000. These values are approximately the median net worth and annual labour income of a US household in 2019, as reported on the most recent Survey of Consumer Finances (SCF)[37]. Results are therefore calculated with a typical US household in mind.

We set the variance of the trade policy shock σ_T^2 = 1and we use results in Exhibit 5 define the value of β_{WMP}. Cumulative abnormal returns are based on five tariff announcements in 2018 and two tariff announcements in 2019 as important trade policy events. While these are not the only important trade policy changes in 2018-2019, it seems reasonable to characterise this period as rather turbulent with a more than one standard deviation trade policy change. Therefore, we consider the average of 3.5 tariff announcements in one year to correspond to a one standard deviation change in $\tilde{T}$. At the same time, we observed a difference of 140bp in abnormal returns around a tariff announcement between trade war and trade peace stocks. Consequently, we set β_{WMP}=0.049, which aligns the sensitivity of the WMP portfolio with our empirical results.

37 - The Federal Reserve Board's triennial Survey of Consumer Finances (SCF) collects information about family income, net worth, balance sheet components, credit use, and other financial outcomes and is often used in household finance to get relevant reference values, see for instance Campbell (2006).

Appendix

To define the value for ε_{WMP}, we base ourselves on the (unreported) annualised variance of 0.0119 of the combined trade peace minus trade war factor in Exhibit 12. Setting $\sigma^2_{\varepsilon_{WMP}}$=0.0095 results in a total WMP portfolio variance of 0.0119 and means that we assume that 20% of this variance is explained by shifts in trade policy.

We consider a range of investors with values for $\beta_Y \in$ [-25,000,25,000]. This means that a one standard deviation shock in $\tilde{T}$ results in a variation in labour income between -42% and 42% of the expected labour income, as presented on the x-axis of Exhibit 13. Our goal is not to pinpoint labour income sensitivity to shifts in trade policy precisely, but rather to show a broad range that covers a large portion of occupations in the economy. While many, for example teachers, will have a β_Y close to zero, employees in certain sectors may have labour income that is highly sensitive to trade policy shocks. For example, international transport firms may be forced to cut staff or go out of business when trade barriers arise, potentially leading to periods of unemployment. Therefore, while we leave a more thorough analysis to future research, it seems reasonable that some extreme cases in the economy will have a sensitivity around the endpoints of our interval.

We also define some additional parameters that do not influence the optimal weight in the WMP portfolio θ^*, but are needed to calculate the ratio $\frac{\bar{W}}{\sigma_W}$. We set σ_{ε_Y}=6,000, which means that a one standard deviation change in non-trade related uncertainty has an impact of 10% on labour income. For the market portfolio, we set expected returns $\overline{R_M}$ =0.10 and variance $\sigma^2_{\varepsilon_M}$=0.04, in line with historical observations shown in Exhibit 24.

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About Scientific Beta

About Scientific Beta

Scientific Beta's aim is to encourage the entire investment industry to adopt the latest advances in smart factor and ESG/climate index design and implementation. Our institution was established in December 2012 by EDHEC-Risk Institute, one of the top academic institutions in the field of fundamental and applied research for the investment industry, as part of its mission to transfer academic know-how to the financial industry. Scientific Beta brings the same concern for scientific rigour and veracity to all the services that it provides to investors and asset managers. We offer the smart factor and ESG/Climate solutions that are most proven scientifically, with full transparency of both methods and associated risks.

On 31 January 2020, Singapore Exchange (SGX) acquired a majority stake in Scientific Beta. SGX continues to support our strong collaboration with EDHEC Business School, and the principles of independent, empirical-based academic research that have benefited our development to date.

Scientific Beta has developed two types of expertise over the years, responding to two of the major challenges that investors face:
- Smart Beta and, more particularly, factor investing.
- ESG, in particular climate investing.

To date, Scientific Beta has made offerings with two major types of climate objective available to investors:

Since 2015, we have offered products with financial objectives that respect ESG and carbon constraints. These correspond to the application of exclusion filters, the design of which allows the financial characteristics of the index to be conserved. This involves reconciling financial objectives and compliance with ESG norms and climate obligations. As such, our Core ESG, Extended ESG and Low Carbon filters can be integrated into smart beta or cap-weighted offerings in line with the financial objectives targeted by the investor.

Since 2021, Scientific Beta has also offered indices with pure climate objectives (Climate Impact Consistent Indices) that enable climate exclusions and weightings to be combined in order to translate companies' climate alignment engagement into portfolio decisions.

Since it was acquired by SGX in January 2020, Scientific Beta has accelerated its investments in the area of Climate Investing as part of the SGX Sustainable Exchange strategy, which is mobilising an investment of SGD20 million. In addition, EDHEC and Scientific Beta have set up a EUR1 million/year ESG Research Chair at EDHEC Business School.

With the aim of providing worldwide client servicing, Scientific Beta has a presence in Boston, London, Nice, Singapore and Tokyo. As of 31 July 2022, our indices had USD52.47bn in assets under replication. Scientific Beta has a dedicated team of 55 people who cover not only client support from Nice, Singapore and Boston, but also the development, production and promotion of our index offering. Scientific Beta signed the United Nations-supported Principles for Responsible Investment on 27 September 2016. We became an associate member of the Institutional Investor Group on Climate Change on 9 April 2021.

About Scientific Beta

Today, Scientific Beta devotes more than 40% of its R&D investment to climate investing and more than 45% of its assets under replication refer to indices with an ESG or climate focus. As a complement to its own research, Scientific Beta supports an important research initiative developed by EDHEC on ESG and climate investing and cooperates with Moody's ESG and ISS ESG for the construction of its ESG and climate indices.

On 27 November 2018, Scientific Beta was presented with the Risk Award for Indexing Firm of the Year 2019 by the prestigious professional publication Risk Magazine. On 31 October 2019, Scientific Beta received the Professional Pensions Investment Award for "Equity Factor Index Provider of the Year 2019." On 2 February 2022, Scientific Beta was named "Best Specialist ESG Index Provider" at the ESG Investing Awards 2022.

Scientific Beta Publications

Scientific Beta Publications

2023 Publications

- Bruno, G., Goltz, F.,and B. Luyten. Firm-Level Exposure to Trade Policy Shocks: A Multi-dimensional Measurement Approach. (June).
- Aked, M. The Three Principles of Climate Impact Investing. (May).
- Aked, M. Navigating the Factor Menu - The Role of Macroeconomic Factors. (February).

2022 Publications

- Christiansen, E. Scientific Beta welcomes the NZAOA's Principles for Net-Zero-Aligned Benchmarks (December).
- Christiansen, E. Financing the Energy Transition: What is the Role of Fossil Fuels Divestment? (November).
- Mauguin, R. Scientific Beta Global Universe. (July).
- Christiansen, E., D. Aguet and N. Amenc. Climate Impact Consistent Indices. (March).
- Esakia, M and F. Goltz. Targeting Macroeconomic Exposures in Equity Portfolios: A Firm-Level Measurement Approach for Out-of-Sample Robustness. (February).

2021 Publications

- Amenc, N., G. Bruno and F. Goltz. Should ESG alpha Really be Positive? Assessing the Five Forces that Drive ESG Investment Returns. (December).
- Mahtani, R. Scientific Beta Enhanced ESG Reporting – Supporting Incorporation of ESG Norms and Climate Change Issues in Investment Management. (August).
- Bruno, G., M. Esakia and F. Goltz. "Honey, I Shrunk the ESG Alpha": Reactions of Investment Professionals (November).
- Amenc, N., F. Goltz, and V. Liu. Doing Good or Feeling Good? Detecting Greenwashing in Climate Investing (August).
- Aguet, D. Protecting your Equity Portfolio Against Inflation. (July).
- Christiansen, E., D. Aguet and N. Amenc. Scientific Beta Core ESG Filter: A Consensus and Norms-Based ESG Investing Approach. (August).
- Christiansen, E. Scoring against ESG? What are Market Participants' Views on ESG Scores? (May).
- Amenc, N., M. Esaki and F. Goltz. When Greenness is Mistaken for Alpha: Pitfalls in Constructing Low Carbon Equity Portfolios. (May).
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- Aguet, D., N. Amenc and F. Goltz. Reconciling Financial and Non-Financial Performance. (February).

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- Christiansen, E. and F. Ducoulombier. Scoring Against ESG? Avoiding the Pitfalls of ESG Scores in Portfolio Construction (December).
- Aguet, D. and E. Orecchini. Examining the Financial Performance and Risks of Smart Beta Strategies (December).

Scientific Beta Publications

- Ducoulombier, F. A Critical Appraisal of Recent EU Regulatory Developments Pertaining to Climate Indices and Sustainability Disclosures for Passive Investment. (December).
- Amenc, N., Christiansen, E. and F. Ducoulombier. ESG and Climate Change Integration Philosophy and Capabilities. (November).
- Amenc, N., Christiansen, E. and F. Ducoulombier. Scientific Beta ESG Index Customisation Capabilities. (November).
- Ducoulombier, F. and V. Liu. Carbon intensity bumps on the way to net zero. (October).
- Ducoulombier, F. Understanding the Importance of Scope 3 Emissions and the Implications of Data Limitations. (October).
- Ducoulombier, F. A Critical Appraisal of Recent EU Regulatory Developments Pertaining to Climate Indices and Sustainability Disclosures for Passive Investment. (October).
- Aguet, D., N. Amenc and K. Schneider. Why Should Investors Stick with their Factor Strategies? (September).
- Korovilas, D. Single-Factor indices. (August).
- Aguet, D. and E. Christiansen. Scientific Beta Core ESG Filter: A Consensus and Norms-Based ESG Investing Approach. (July).
- Aguet, D., N. Amenc and E. Shirbini. Scientific Beta Factor Analytics Services (SB FAS) - A New Tool to Analyse and Improve your Portfolio. (June).
- Amenc, N., E. Christiansen, F. Ducoulombier, F.Goltz, and V. Liu. ESG Engagement and Divestment: Mutually Exclusive or Mutually Reinforcing? (May)
- Amenc, N. and D. Korovilas. Robustness of Smart Beta Strategies: a Competitor Overview. (May).
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- Aguet, D., N. Amenc and F. Goltz. Managing Sector Risk in Factor Investing. (January).
- Aguet, D., N. Amenc and F. Goltz. What Really Explains the Poor Performance of Factor Strategies Over the Last Four years? (January).

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