Who wins and who loses from trade agreements? Stock market reactions to news on TPP and TTIP

Andreas Dür and Lisa Lechner
University of Salzburg and University of Innsbruck

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Abstract

Which companies gain and which companies lose from trade agreements? In contrast to a view that sees the largest companies as the main beneficiaries of trade agreements, we argue that medium-sized companies gain most from them. Moreover, we examine whether more capital-intensive and more diversified companies benefit more than other firms. Our empirical test relies on a dataset with daily firm-level stock price data for close to 4,000 US companies over the period 2009-2016. Concretely, we assess how the shares of different types of firms reacted to news on the (lack of) progress of the negotiations aimed at concluding the Transpacific Partnership (TPP) and Transatlantic Trade and Investment Partnership (TTIP). We find support for the view that medium-sized companies win most from trade agreements. Besides speaking to the literature on the distributional effects of trade agreements, the paper makes a contribution to recent research on the role of firms in international political economy and the stock market consequences of political events. It also presents a novel approach to measuring progress and stagnation in international trade negotiations using computational text analysis.

1 Introduction

Developed countries currently witness a backlash to globalization. After many years in which they have moved towards ever more liberal trade and economic relations, we now see at least a partial reversal of these policies. In Europe, Brexit and strong opposition to the Transatlantic Trade and Investment Partnership (TTIP), a potential trade agreement between the United States and the European Union (EU) that did not materialize, epitomize this globalization backlash. In the United States, the election of Donald Trump as president and the decision to withdraw from the Transpacific Partnership Agreement (TPP) are cited as examples of this reaction to globalization.

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Many researchers and observers use the distributional consequences of trade policy choices to explain this development (Rodrik, 2018; Saval, 2017). The deep trade agreements that countries enter into, the argument goes, mainly benefit the already wealthy, while hurting the relatively less well-off. As a result, the latter increasingly turn against globalization in general and trade agreements in particular.

But what are the actual distributive consequences of trade policy choices? We contribute to answering this question by focusing on which companies gain or lose from trade agreements. Building on the so-called "new new trade theory" (Ciuriak et al., 2015; Melitz and Redding, 2014), we present three expectations on the relationship between firm characteristics and trade agreements. The first argument deals with differences in company sizes. Critics of trade agreements see the largest multinational companies as their main beneficiaries. Some academic research supports this view (Baccini et al., 2017; Breinlich, 2014). Others take a more benign view. Illustratively, supporters of TTIP predicted that this agreement would mainly benefit small and medium-sized companies. The United States Trade Representative Mike Froman, for example, stated: "Among the many beneficiaries of TTIP, perhaps small businesses stand to gain the most" (quoted in Workman, 2014). We side with the second view in arguing that the largest companies engage in international trade even given existing barriers. These barriers, however, are prohibitive for slightly smaller companies. The reduction of barriers, then, mainly benefits these medium-sized companies, by allowing them to become active participants in international trade. Furthermore, we expect that capital intensive and diversified companies gain more from the conclusion of trade agreements than other companies.

We test our argument with a stock market event study that relies on daily firm-level stock price data for 3,926 US companies over the period of 2009-2016. Specifically, we assess how the shares of different types of firms reacted to news on the (lack of) progress of the negotiations aimed at concluding the TPP and TTIP. TPP was supposed to be a trade agreement among twelve countries in the Pacific region, including the United States. It failed when the United States decided to withdraw its signature from the agreement in early 2017. TTIP's aim was to facilitate trade between the United States and the EU. Formal negotiations for TTIP started in 2013, but the negotiations stalled in 2016.

Our study is not the first one to examine the stock market impact of trade agreements. More than two decades ago, Thompson (1993, 1994) analyzed how the Canada - United States Free Trade Agreement affected the market value of Canadian companies. Breinlich (2014) reanalyzed the same agreement from within the framework of new new trade theory. Whereas these studies just focused on a single country, Rodriguez (2003) investigated the (sectoral-level) stock market impact of the North American Free Trade Agreement (NAFTA) in all three participating countries. Moving to a quite different context, Parinduri and Thangavelu (2013) studied the impact of the United States - Singapore free trade agreement. Looking at a disintegration event, Davies and Studnicka (2018) assessed the impact of the exit of the United Kingdom from the EU on stock prices. Finally, Moser and Rose (2014) studied the impact of a large number of preferential trade agreements on aggregate national stock market indices.

We make several contributions to this state of the art. First, whereas all the studies that looked at firm-level effects focused on a single trade agreement, we include two agreements in our analysis. This increases the robustness of our results, and also allows us to check for any differences depending on agreement characteristics. Second, we study both "positive" (i.e. pro-integration) and "negative" (i.e. disintegration) events in a single study. Doing so allows for a much better empirical test of our expectations. Third, we use automated text analysis to identify the relevant events. Most previous studies either only considered a single event (mainly the signature of a trade agreement) or very few, manually selected events.[1] The approach used in these studies faces the problem that investors may already become convinced that an agreement is very likely before the agreement is actually signed. The news effect of the signature hence may be very small. By focusing on a larger number of events all through the process of negotiations, we manage to remedy this problem.

In making and testing our argument, the paper also contributes to a broader strand of research that uses stock market data to assess the impact of political events (Bechtel and Schneider, 2010; Schneider and Troeger, 2006; Wolfers and Zitzewitz, 2018). Furthermore, we contribute to a growing literature on the role of firms in international political economy (Jensen et al., 2015; Milner, 1988; Osgood, 2018). Finally, we advance research on computational text analysis in political science (Monroe and Schrodt, 2008; Wilkerson and Casas, 2017) by showing how this method can be used to capture progress and failure of international trade negotiations.

2 Argument

Which companies gain and which companies lose from trade agreements? Traditionally, the expectation was for companies in import-competing sectors (supposedly sectors in which a country has no comparative advantage) to lose and for companies in exporting sectors (sectors in which a country has a comparative advantage) to gain from agreements that lead to reciprocal trade liberalization (Dür, 2010; Gilligan, 1997; Hiscox, 2001). According to this view, the main cleavage over trade policy exists between industries. For example, firms in the manufacturing sector may gain, whereas firms in the textile sector lose from an agreement that liberalizes trade. If this view is correct, the impact of trade agreements can be analyzed at the level of sectors, as all firms in a sector face the same consequences from trade policy choices.

In line with what has been called "new new trade theory" (Ciuriak et al., 2015; Melitz and Redding, 2014), however, more recent research has shown much variation in the consequences of trade liberalization or other trade policies across firms within the same industry (Baccini et al., 2017; Breinlich, 2014; Melitz and Redding, 2014; Osgood, 2017). According to this view, a sole focus on sectors obscures interesting variation across firms. Within the same sector, some companies may benefit from a specific trade policy choice, whereas others lose. Increased trade leads to a reallocation of production within the same sector from firms with relatively low productivity (which also tend to be smaller companies) to firms with higher productivity (which tend to be the largest companies in a sector). We draw on this newer strand of literature when proposing a set of hypotheses on the distributional effect of trade agreements at the level of firms.

Throughout the following discussion, we build on the assumption that investors on stock markets are aware of the effects of trade (agreements) on different firms.[2] To make informed

[1] As an exception, Rodriguez (2003) included no fewer than 30 events, both positive and negative, in his analysis. However, he did not assess firm-level effects, but sectoral-level effects.

[2] Similar assumptions underlie all event studies. (See, for example, Armstrong et al., 2010; Grossman et al.,

investment decisions, they follow the news on trade negotiations. When the news indicate that the chances for a successful conclusion of a negotiation increase, they buy shares of companies that they expect to benefit from the agreement and sell shares of companies that they expect to be hurt by the agreement. If the news indicate that the chances for a successful conclusion of the negotiations decrease, the investors will do just the opposite – sell the shares of the companies that would benefit from the agreement and buy the shares of the companies that would lose from the agreement. Selling means that the price of the shares decreases, whereas buying means that the price of the shares increases. At any time, therefore, the value of a stock internalizes all the information available to investors and hence takes into account expected future changes in profitability.

More formally, investors assign an expected value to company i at time T in the presence of a trade agreement (V_{iT}^{ta}) and a value at time T in the absence of such an agreement ($V_{iT}^{no\_ta}$). To be able to determine V_{iT}^{ta} and $V_{iT}^{no\_ta}$ they need to know how a trade agreement affects future earnings per share via factors such as company sales, market share and profitability. They then buy or sell shares of the company until the share price of the company equals the (discounted) expected value of the company given the information available at the moment ($E[V_{iT}|I_t]$):

$$E[V_{iT}|I_t] = p_t V_{iT}^{ta} + (1 - p_t) V_{iT}^{no\_ta},$$

where I_t is the information available to the investors at time t and p_t is the probability that the agreement will be implemented at time T in the future. New information changes investors' assessment of p_t and hence the value they assign to company i, making them either buy or sell shares.

The starting point for our argument is that, across all sectors, relatively few firms actually engage in international trade. Illustratively, for the United States Bernard and Jensen (2007, 109) showed that less than a fifth of all firms in the manufacturing sector export goods (see also World Trade Organization, 2008). Better foreign market access then only benefits a subset of firms within each sector. The same applies to importing: again, only a minority of companies source imports abroad and hence benefit from lower domestic trade barriers. As there is much overlap across the two sets of firms - those that export and those that import - most companies are not directly affected by trade liberalization.

Of course, modern trade agreements do more than just liberalize trade. They also protect foreign direct investments (FDI) and intellectual property rights, and even affect domestic regulations via regulatory cooperation (Dür et al., 2014). From the home country perspective, the protection of FDI mostly matters for a small number of companies, as only few companies tend to produce abroad. In the host country, a larger number of companies may face increased competition from foreign FDI as a result of a trade agreement. In an agreement between developed countries, provisions concerning the protection of intellectual property rights generally do not matter much, but they can affect firms in agreements with countries at lower levels of development. Regulatory cooperation can have a broader impact, but in practice regulatory cooperation does not actually change domestic rules, but at most offers some form of mutual recognition.

1989). Wolfers and Zitzewitz (2018), however, show that sometimes investors incorrectly anticipate future market responses.

Moreover, via several mechanisms trade agreements can indirectly matter for companies that neither engage in international trade nor invest abroad. Companies lose from trade liberalization if they now face competition from abroad for the goods they produce or the services they provide. Or they can benefit from trade liberalization if their output is used as input in new exports. Trade liberalization also affects the costs of factors of production, which matter for all firms in an economy. In fact, in the model put forward by Melitz and Redding (2014), the reallocation of resources across companies that results from trade liberalization mainly works via an increase in the price of labor.

Finally, trade agreements matter for all companies via their impact on economic growth. The deep agreements that currently are negotiated generally increase participating countries' gross domestic product. However, the macroeconomic impact of many trade agreements is small, especially of those that are signed among minor trading partners. In any case, this impact via economic growth should be relatively homogenous across firms.

Keeping all of this in mind, which are the firms that benefit most from a new trade agreement? An argument can be made that the benefits should mainly accrue to the largest firms in an economy. As stated above, only a minority of firms actually export their goods or services. Those that do tend to be larger and more innovative than those that do not. For example, manufacturing exporters from the United States are twice as large in terms of employment than otherwise equal firms that do not export (Bernard and Jensen, 2007, 110). The most prominent explanation for this observation is that firms have to pay a fixed entry cost when they want to export. Only for the most profitable companies is it worthwhile to pay this entry cost. Just as exporting, sourcing abroad is mainly undertaken by large companies (Bernard and Jensen, 2007). This is so because the fixed costs of establishing a supply chain are relatively high, not least because the relationship-specific investments for both buyers and sellers of intermediates are high (Antràs and Staiger, 2012, 3141). Finding a seller then is a tricky task. Only for large firms the lower variable costs of foreign suppliers outweigh the higher fixed costs of establishing an international supply chain (Helpman et al., 2004). The same logic applies to foreign direct investments: again, only the largest companies tend to invest abroad. So overall large firms should benefit from trade agreements and smaller ones should lose.

A few studies actually find empirical support for this expectation (Baccini et al., 2017; Breinlich, 2014). Baccini et al. (2017) arrive at this result by assessing the impact of tariff cuts agreed upon in trade agreements on the exports of affiliates of American companies back to the United States. The focus on tariff reductions and (goods) trade, however, means that this study captures only a small part of what modern trade agreements really are about. By design, moreover, it only assesses the consequences for multinational companies, whereas also companies that have no foreign affiliates may benefit (or lose) from a trade agreement. Breinlich (2014) also uses tariff cuts to assess the impact of a trade agreement – in this case the Canada‚ÄìUnited States Free Trade Agreement (CUSFTA) of 1989 – on firms. But the main event analysed in the paper relates to the chances of an election victory of the Conservative Party in Canada. Such an election victory could matter for firms in many ways, not only via greater chances of the ratification of CUSFTA. Clearly, then, these studies do not yet fully settle the question of the distributional impact of trade agreements on firms.

In fact, there is an alternative perspective on the impact of firm size on the benefits of trade agreements. Proponents of such agreements tend to argue that they mainly benefit small and medium-sized companies (European Commission, 2013; Persin, 2011; Workman, 2014). The logic of this argument is straight-forward: although the fixed costs of exporting, importing or investing abroad under normal trading conditions are high, the largest and most productive companies can engage in all of these activities even in the absence of a trade agreement. By reducing competition, barriers that keep the fixed costs high can even benefit them. Trade agreements not only reduce variable costs such as tariffs, but also fixed costs, such as customs formalities, regulatory barriers or risks to foreign direct investments. The reduction of these fixed costs should mainly benefit the mid-sized companies that in the absence of a trade agreement are barred from directly participating in international trade and investments. In the words of Workman (2014), "A TTIP agreement that eliminates duplicative regulatory requirements and harmonizes equivalent standards would have an outsized positive impact on SMEs [small and medium-sized enterprises]." In fact, trade liberalization might allow some firms that previously only produced for the domestic market to become exporters.

Independent of whether this increase in exports is due to trade creation or to trade diversion, these firms are likely to reap some gains from doing so, as exporters have been shown to grow more rapidly than non-exporters (Bernard et al., 2003; Kasahara et al., 2013). What is more, the productivity gains from moving from non-exporting to exporting are largest for plants that were relatively less productive at the starting point (Lileeva and Trefler, 2010). Finally, also the chances of survival are higher for firms that export, import or engage in two-way trade (Wagner, 2012, 256-261). A trade agreement thus creates particularly large benefits for firms that manage to become exporters or importers. As we expect that especially medium-sized companies change from buying and selling locally to operating internationally, the benefits should be particularly visible for the latter group. Hence our first hypothesis reads as follows:

H1: The share prices of medium-sized companies benefit (suffer) most from events that make the conclusion of a trade agreement more (less) likely.

Recent research has also shown that international trade is inherently more capital-intensive than the supply of goods to the domestic market (Ciuriak et al., 2015; Matsuyama, 2007). This contradicts traditional theories of trade, which expected that some countries (namely capital-rich ones) export capital-intensive goods and other countries (namely labor-rich ones) export labor-intensive goods. With trade inherently biased towards capital-intensive goods and services, capital-intensive companies should have an advantage in terms of reaping gains from trade agreements. We thus also expect:

H2: The share prices of capital-intensive companies benefit (suffer) most from events that make the conclusion of a trade agreement more (less) likely.

Finally, we expect that the companies that will be best situated to gain from a new trade agreement are those that are active across several sectors. These diversified companies have a greater ability to take advantage of new opportunities that open up as a result of such agreements, or to shift focus away from products where trade agreements increase foreign competition.

Our third expectation thus reads:

H3: The share prices of companies that are diversified benefit (suffer) most from events that make the conclusion of a trade agreement more (less) likely.

3 Research design

We test our argument relying on the negotiations for TPP and TTIP. The former involved up to twelve countries, including highly developed countries such as Japan and the United State and developing countries such as Malaysia and Vietnam. The negotiations started in 2008 and continued until 2015, when a draft agreement was reached after 19 negotiation rounds. A very broad agreement, covering everything from tariff reductions to the protection of intellectual property rights and investments, was signed in 2016. In late 2016, the then President-elect Donald Trump announced that he would withdraw the signature by the United States. The eleven remaining countries eventually moved ahead without the United States. The TTIP negotiations between the United States and the EU started with the establishment of a High Level Working Group on Jobs and Growth in November 2011. Based on the report produced by this working group, formal negotiations for an agreement started in early 2013. Despite many negotiation rounds, no agreement could be reached on TTIP, and the negotiations were suspended when the Trump administration took over from the Obama administration in early 2017.

Both negotiations went through many ups and downs, making it possible to assess the impact of news on their progress or failure on companies' share prices. These ups and downs were not only produced by the willingness of the negotiation parties to make concessions, but also by the reaction of the public. Both TPP and TTIP faced considerable public opposition in some countries, with this opposition contributing to their final demise. The two negotiations are also ideal for testing our argument as they are sufficiently important for it to be plausible that they had a detectable impact on stock prices. All trade agreements should matter at least for some companies (as otherwise they are unlikely to be signed), but an event study is not able to estimate these effects if only few companies are affected, for example because the agreement is between two countries with only weak trade links between them. For reasons of data availability, we focus on companies that have their headquarters in the United States. Since the depth of the American capital market is unrivaled, concentrating on the United States also has substantive benefits.

3.1 Dependent variable

The dependent variable captures the abnormal returns for companies – that is the difference between their actual stock price change and the one expected given previous performance or overall market movement – around a series of important events characterizing the TPP and TTIP negotiations. Worldscope provides data on 3,926 companies that have their headquarters in the United States and that are listed on a stock exchange (mainly NASDAQ and the New

York Stock Exchange).[3] To generate a company's abnormal returns, three standard event-study methodologies exist: market adjusted models with in-sample estimation, market adjusted models with out-of-sample estimation, and mean adjusted models (MacKinlay, 1997). In our baseline model, we rely on the market adjusted approach with in-sample estimation[4], but we employ the other two methodologies in robustness checks.[5]

The market adjusted models are calculated with the share price as dependent variable and a broad-based stock index as predictor:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} (+\beta_e E_t) + \epsilon_{i,t},$$

where $R_{i,t}$ is the return for a specific firm at time t, $R_{m,t}$ is the return on the market portfolio at that same time, and E_t represents a dummy that is 1 if t falls into the estimation window and 0 otherwise. We take the S&P 500 to measure the market return, that is $R_{m,t}$. The event dummy is only relevant in the within-sample estimations, where we concatenate the estimation period ($t-120$ to $t-2$) and the event period ($t-1$ to $t+5$[6]). Starting the estimation period at $t-120$ makes sense given the double objective of having sufficient information to estimate the model and not introducing too much noise in the model. We use a 7-day event period since markets are unlikely to efficiently price in new information in a single day.[7] The coefficient β_e then represents the (cumulative) abnormal return measure ($CAR_{i,T}$), which is the value of the dependent variable for firm i and event T. The advantage in using this model is that we get significance levels for the event coefficient β_e, which informs us whether a company's returns during the event period were statistically significantly different from its expected returns.

For the out-of-sample estimation we also use the period from 120 days before an event until two days before an event as estimation window. The α_i and β_i that we receive from this model then allow us to calculate the expected return for a firm at time t. The abnormal return for each company is the difference between the actually observed return at time t and the expected return at time t:

$$AR_{i,t} \equiv R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}$$

We again cumulate these abnormal returns starting one day before an event and ending five days after the event as follows:

$$CAR_{i,T} \equiv \sum_{T-1}^{T+5} AR_{i,t}$$

In addition to the just presented market adjusted models, we calculate $CAR_{i,T}$ relying on the mean adjusted model, which assumes that the expected return is constant over time, but varies across securities (Brown and Warner, 1980, 1985). In essence, the model subtracts the mean return of a respective security over the estimation period (again ranging from t_{-120} to t_{-5}

[3] Not all of these companies are listed on a stock exchange in the United States. In robustness checks, we drop all those companies that are only listed abroad.

[4] This is also the approach used in a recent study by Davies and Studnicka (2018).

[5] For the empirical implementation, see our R-package estudy2Helper.

[6] We skip non-trading days, which means that $t-1$ refers to t minus one trading day and $t+5$ to t plus five trading days.

[7] We alter the time span of the even period for this and the following measures in the robustness checks.

from the return over the period t_{-1} to t_{+5}, which results in abnormal returns. Then, similar to above, we take the sum of the calculated abnormal returns to receive $CAR\_mean_{i,T}$.

3.2 The predictors

The main explanatory variable that we are interested in are events that indicate progress or failure of the TPP and TTIP negotiations. Rather than manually selecting some events, we decided to rely on the automated analysis of newspaper reports. The main advantage of our approach is that we do not identify turning points in a post-hoc manner that might not have been identifiable as such to contemporary observers. Rather, we rely on information (and the interpretation of that information as indicating progress or failure) available at the moment of the event.

We retrieved in the US published newspaper reports that represent the starting point for our approach from LexisNexis using the following algorithms:

> "DATE(=[year]) and (HEADLINE(TPP) or HEADLINE(Trans-Pacific Partnership) or HEADLINE(Transpacific Partnership)) and ((BODY(Trans-Pacific Partnership) or BODY(Transpacific Partnership) or BODY(transpacific) or BODY(TransPacific) or BODY(trade agreement)) or (HEADLINE(Trans-Pacific Partnership) or HEADLINE(Transpacific Partnership) or HEADLINE(transpacific) or HEADLINE(TransPacific) or HEADLINE(trade agreement)))"

> "DATE(=[year]) and (HEADLINE(TTIP) or HEADLINE(Transatlantic Trade and Investment Agreement) or HEADLINE(Transatlantic Trade Agreement))"

The newspaper search on TPP had to be more restrictive as TPP is an acronym for several other, not trade-related topics. We further restricted our sample to articles printed in outlets published in the United States. Using this approach, we arrived at 2,359 newspaper articles on TPP published between 1 January 2009 and 31 December 2017 and 1,193 newspaper articles on TTIP that were published between 1 January 2013 and 31 December 2017.

Figure 1 shows the number of articles over time. News on TPP peaked at five moments: at the end of 2009 when the United States entered the TPP negotiations, at the end of 2012 during intense negotiations and when Canada and Mexico were invited to join the negotiations, in January 2016 when the final TPP text was released, in January 2017 when the US withdrew from TPP, and at the end of 2017 as the eleven remaining members of TPP announced progress in their negotiations.

Four peaks and one longer stretch of intense news reporting characterize the development of the TTIP negotiations. The reports in July and August 2013 deal with the first round of negotiations over TTIP. At the beginning of 2014, the EU Commission consulted the public on provisions in TTIP on investment and investor-state dispute settlement. The following negotiation rounds were characterized by tensions over investment issues, standards, and agriculture. On 9 October 2014, the European Commission published the TTIP negotiation mandate. News on the negotiations peaked with the British referendum over EU membership in June 2016. In November 2016, large protests against TTIP hit the headlines. In the same month, also the elections in the United States increased reporting on TTIP.

Our analysis, however, calls for more than just a measure of attention to the negotiations. What we need is a measure of whether the news are positive or negative with respect to the chances of concluding the deals. In other words, we need a measure of sentiment on a dimension from progress to stagnation.

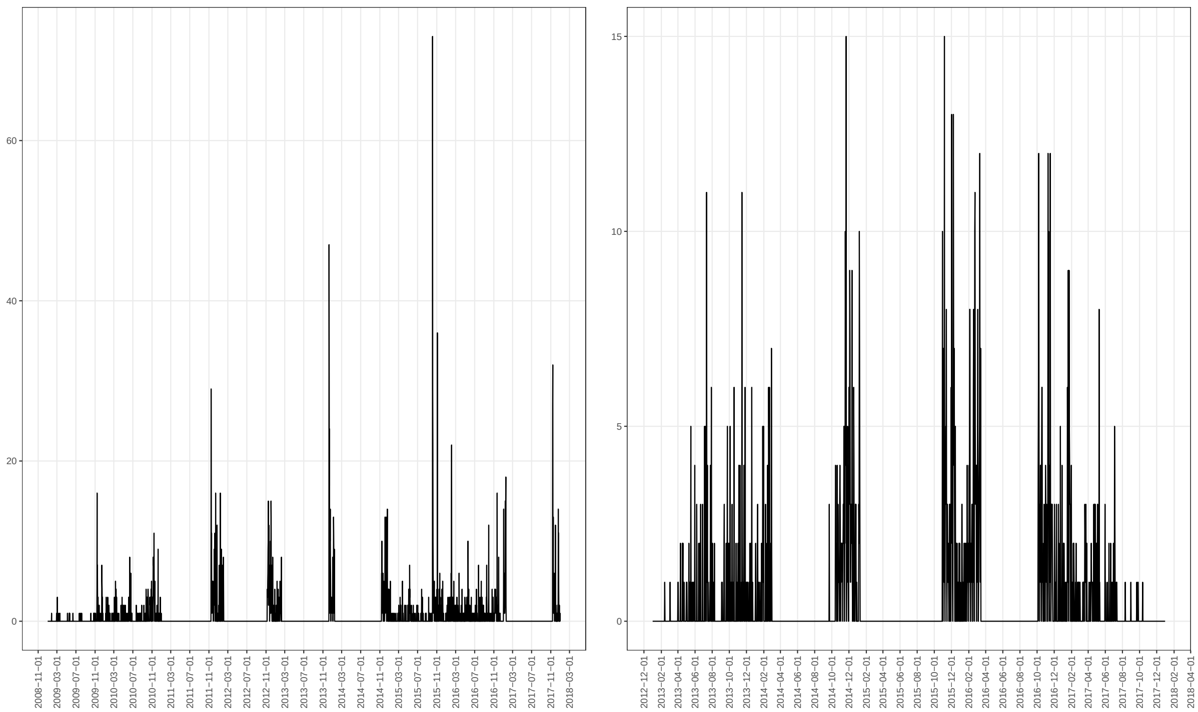


Figure 1: Newspaper articles on TPP (left) and TTIP (right) over time

We decided against manually coding all articles for several reasons. For one, given the number of articles in our dataset, this would have been an enormous task. Moreover, manual coding raises the question of reliability. Manual coding thus would have required double coding all articles, making the task at hand even larger. Finally, manual coding does not allow for any simple scaling up of the study, for example to study the effects of other trade negotiations. A computational analysis of the texts helps on all of these issues.

When it comes to the question of which computational method to pick, several options exist. The computationally simplest approach relies on a dictionary, which includes character strings and sentiment values that classify text (Krippendorff, 2013). Yet, professional linguistic dictionaries with values exist only for the classification of positive versus negative texts. When using existing dictionaries, we thus would have to assume that progress equals positive sentiments and stagnation negative sentiments. Positive words such as "good", "great" or "fabulous", however, seem to cover only parts of our concept of progress. Sentences such as "The parties finished negotiations" would be classified as negative using the positive versus negative classification, because the word "finish" comes with a negative loading. Yet, for the purpose of this study the respective sentence should be understood as indicating progress in trade negotiations. To be able to rely on a dictionary-based approach, we thus would have to generate our own dictionary. Haselmayer and Jenny (2017), for instance, did so by relying on large-scale crowd coding of text segments to generate sentiment values of texts and subsequently of words. However, we would need to code a lot of texts to generate a useful dictionary. Haselmayer and Jenny (2017) had ten coders each code 13,000 randomly selected sentences. Such a large-scale coding undermines the above mentioned advantages of automated processes in our research design.

An alternative approach is to rely on supervised machine learning algorithms (Burscher et al., 2014, SML). Kananovich (2018) applies this to a similar problem as ours, namely the classification of newspaper articles. SML learns to classify text on a subsample of text segments that were coded by humans (Grimmer and Stewart, 2013). This subsample represents the training set from which the computer learns and infers the coding for the remaining, not yet classified documents. This is the approach that we adopt in this paper.

Hence, we started with the manual coding of 500 newspaper texts. We asked the coder to assign a value of 1 if the text deals with events that have the potential to increase the likelihood of a successful conclusion of the negotiations. A text receives the value of -1 if it captures events that have the potential to hinder or delay the successful conclusion of the negotiations. This includes actors, such as politicians or interest groups, coming out in opposition to the agreement. A value of 0, finally, indicates a text that captures neutral events that relate to neither progress nor stagnation of the negotiations. To make this manual coding reliable, three coders looked at a subset of 100 texts to calibrate the coding. We then took 80 percent of the 500 coded texts to train the data and 20 percent to test the performance of approaches.

To make a computational analysis possible, we had to prepare and clean the texts. The aim of the preprocessing was to reduce noise while keeping the meaning of the text.[8] First, we lower-cased all words and removed punctuation. Next, we dropped extra and superfluous whitespace. Third, we lemmatized words to reduce unnecessary complexity in the text. Lemmatization is an algorithmic process that reduces the word to the *lemma*, which keeps the word's intended meaning. In contrast to stemming, lemmatization identifies the position of the word and infers therefrom the meaning. This means that lemmatization is less prone to delete substantial information from the text than stemming. We used a tool called Treetagger by Schmid and Schmid (1994) to realize the lemmatization. If the tool fails to find an appropriate lemma, we used the algorithm proposed by Porter (1980) to arrive at the word stem. Fourth, we compounded words that belong together.[9] This represents another important step to avoid a distortion of the meaning in the text. Since the machine learning algorithms rely on a bag-of-words approach, the creation of n-grams is indispensable to maintain the meaning of the texts. The input to the machine learning algorithms are document-term matrices with both 1-gram and 2-grams of the texts.

Similar to Kananovich (2018), we trained eight machine learning algorithms on these texts: support vector machine, generalized linear model, maximum entropy, scaled linear discriminant analysis, bagging, random forest, decision tree, and boosting.[10] We selected these algorithms to cover a wide range of assumptions and performance characteristics. Decision tree and random forest, for instance, are effective in high dimensions. Generalized linear models are better dealing

[8] We used the following R-packages for preprocessing: *quanteda*, *stringr*, and *treetagger*.

[9] The compound words (after lemmatization) in the newspaper articles are the following: trans-pacif partnership agreement, trans-atlantic, work group, trade commission, transatlantic trade agreement,civil society, european commission, european parliament, karel de gucht, michael froman, Atlantic council forum, unite kingdom, trade union, g20 summit, g8 summit, trade representative, free trade, trade area, trade talk, trans-pacif partnership, united state, trade representative, trade rep, human right, trade deal, trade chief, council of the european union, environmental protect, social right, labour standard, environmental protection, intellectual property right, european union, investor abitration, trade in good, trade in service, preferential trade agreement, free trade agreement,trade agreement, donald trump,barack obama,hillary clinton,angela merkel, gernd lang, justin trudeau, shinzo abe, new zealand, van hollen, de gucht.

[10] For details on the different algorithms see Gibbons et al. (2017). The R-package *RTextTools* provides an efficient infrastructure to work with these algorithms.

with only few dimensions but are computationally effective. In contrast, the support vector machine model requires more computational power; yet it often delivers robust results. All of these algorithms are based on a single strong learner, which aims at the maximization of the correlation with the true classification. Boosting, in contrast combines multiple weak learners, where each is only slightly correlated with the true classifier. Three of the algorithms did not run on a computer with 32 GB RAM and 16 cores because of a lack of memory. Thus, we have results for five algorithms.

By dint of the test sample (20 percent of the human coded sample), we assess the performance of these algorithms. For this purpose, we rely on three measures: precision, recall, and F-score. Precision measures the proportion of predicted values that match the human coding. Recall represents the proportion of the correctly predicted values. The F-score captures the harmonic average of precision and recall with a value of 1 being perfect precision and recall and 0 worst precision and recall. Table 1 shows the results of these performance checks. We take the two best-performing algorithms, namely support vector machine and random forest, to classify the remaining documents as indicating progress or stagnation. If these two algorithms agree, we take the respective value; if not, we use the value of the algorithm that was certain with a probability greater than 80 percent. In case both algorithms were certain with a probability greater than 80 percent and calculated different results or if both algorithms were uncertain with a probability lower than 80 percent and disagreed, we take a value of 0, which is our neutral category.

Table 1: SML Performance measures

Algorithm	Precision	Recall	F-score	Ranking
Support vector machine	0.72	0.55	0.48	1
Random forest	0.61	0.38	0.32	2
Maximum entropy	0.51	0.56	0.49	3
Generalized linear model	0.44	0.39	0.38	4
Boosting	0.34	0.34	0.34	5

For our analysis, we need one value capturing the progress or stagnation of an event day. This requires an aggregation of the individual newspaper values per agreement and per day. At this point, we dropped event days that covered less than four TTIP articles or less than four TPP articles. The risk of analyzing days with too few articles is that the event is captured wrongly and that we include event-dates that are irrelevant to investors. The assumption here is that if a significant event happens, more than three newspapers report on the issue. To aggregate values for newspaper articles to values for event dates, we first weight newspaper-article-values by their probability and use these weighted values to calculate the average per day. Events with a time difference of seven or fewer days are treated as one event, where we calculate the weighted value across all these days and flag the result with the minimum date.[11] This is important to avoid overlaps in the analysis. We then selected the 8 most probable progress events and all 3 stagnation events.[12] Finally, we rounded the results so that we have the following values: -1 (stagnation) and 1 (progress). We also checked whether there was any overlap between TPP

[11] As we take a lead of five days and a lag of one day for the calculation of the cumulative abnormal returns, seven days represents the minimum required distance between two events.

[12] 8 to 3 represents the true distribution in the data. This information stems from the manual coding sample. The number results from the fact that the SML output covered 3 stagnation events for each agreement. Hence, we took all stagnation events and defined the number of progress events therefrom.

and TTIP events, but this was not the case.

Table 2 shows the result of this process. Most of these events and their coding as progress or stagnation event seem plausible. In October 2015, for instance, the TPP negotiations were concluded and in February 2016 TPP was signed formally. Both events are classified as progress event in our sample. In September 2016, Vietnam decided to delay the ratification of TPP. This event signals stagnation in the dataset. In November 2014, the first protests on TTIP emerged and we see a stagnation event in our data. Yet, we are surprised by the progress classification of 4 December 2014, which is the date where one million signatures were reached by the anti-TTIP campaign.

Table 2: Progress versus Stagnation Events

Date	Agreement	Value
2009-11-14	TPP	1
2010-11-14	TPP	1
2011-12-09	TPP	1
2011-12-14	TPP	1
2014-12-05	TPP	1
2014-12-19	TPP	-1
2015-10-06	TPP	1
2016-02-04	TPP	1
2016-09-29	TPP	-1
2016-11-22	TPP	-1
2013-10-18	TTIP	-1
2013-11-26	TTIP	1
2014-02-21	TTIP	1
2014-11-18	TTIP	-1
2014-12-04	TTIP	1
2015-11-12	TTIP	1
2015-12-07	TTIP	1
2016-02-18	TTIP	-1
2016-11-09	TTIP	1
2016-11-17	TTIP	1

Figure 2 shows how these events play out on the stock market returns of firms. For both agreements, the strongest reactions happened toward the end of the negotiation phase. Stocks of 560 firms reacted strongly to the signature of TPP on 3 February 2016. Surprisingly, the majority of companies experienced a negative effect on their stock market returns. Contrarily, in December 2014, when the US government spoke up for fast-tracking TPP, stock market returns of nearly 400 companies increased. At the end of 2015, when the European Union presented its new trade and investment policy strategy entitled “Trade for all”, stocks of 206 US companies reacted negatively. Similarly on 9 November 2016, when EU policy representatives announced a break in the TTIP negotiations, stock returns of 131 dropped. At the same time, however, the stocks of 1,302 companies gained in value.

Although it is interesting to see that TTIP and TPP events had a significant, yet sometimes surprising, effect on US companies, the question of who gains and who looses remains open.

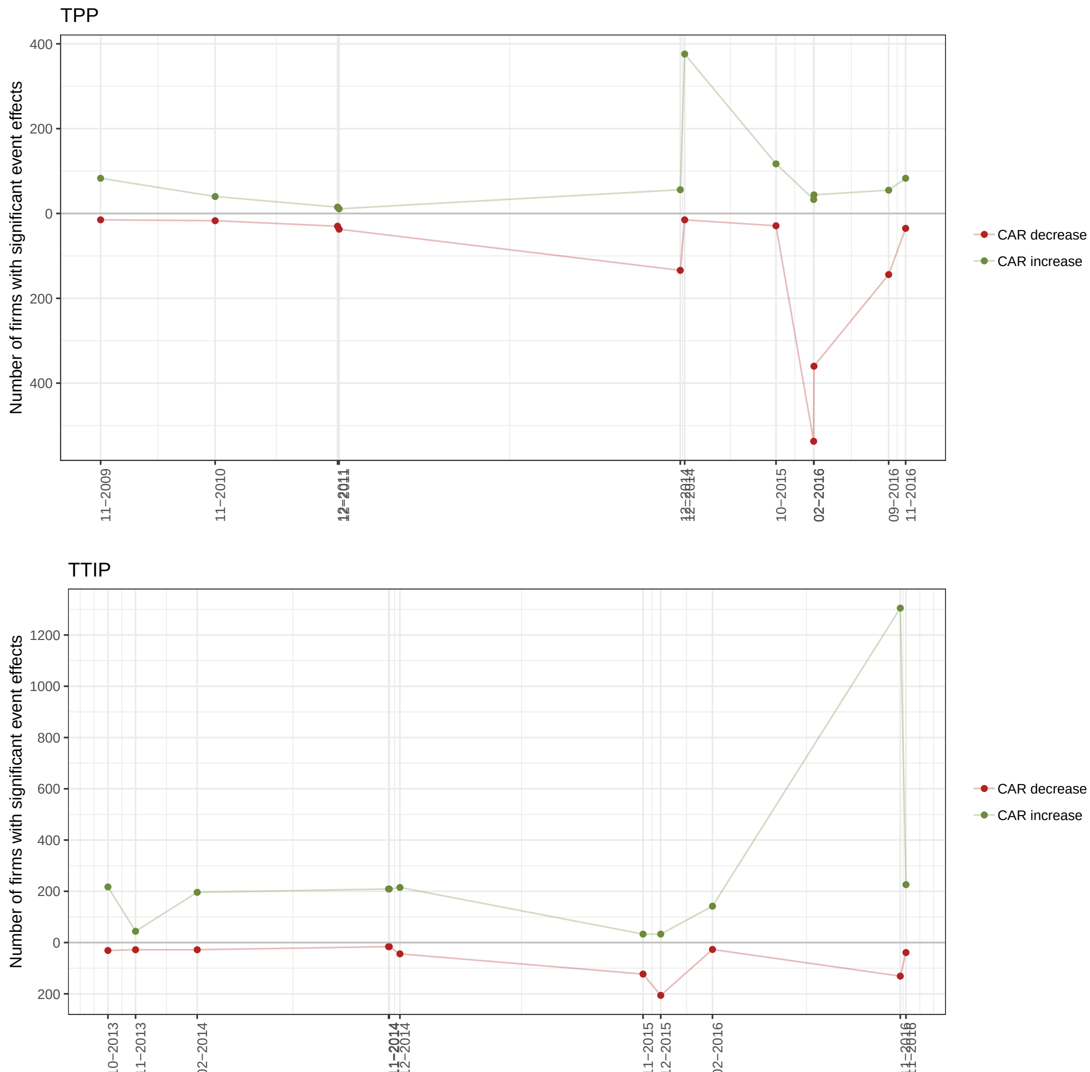


Figure 2: Count of firms with signficant event effects

To tackle this question, in the following analysis we interact the *progress versus stagnation*-dummy with several firm characteristics. H1 makes us expect that the impact of these events on firms differs depending on firms' size. We use the (natural logarithm of) firms' market value (from Worldscope) as a proxy for a firm's size (*Market value*). We chose market value rather than market capitalization, as it takes into account several additional factors that go beyond stockholder equity, such as outstanding bonds, long-term growth potential, corporate depth, taxes and interest payment. Hence, market value is seen as capturing the size of companies better than market capitalization. However, the two variables are highly positively correlated (r=0.98). At this point it is important to note that our sample only includes companies listed on the stock market, which results in a bias towards large companies. We still have much variation in terms of company size in the dataset.

In H2 we refer to the capital intensity of firms. Capital intensity means how much capital a company uses relative to labor in its production process. Using data from Worldscope, we measure this variable by dividing a company's market value by its number of employees (*Capital intensity*). As could be expected, the values on this variable are particularly high for companies in the mining and finance sectors, and particularly low in the retail sector.

H3 draws attention to the extent to which the companies are diversified. To operationalize this variable, we use the number of sectors at the 4-digit level of the Standard Industry Classification (SIC) in which the companies are active (as coded in the Worldscope database) (*Diversification*). This variable ranges from 1 to 8, with the modal value being 2. In 2010, Microsoft Corp. is coded 8 on this variable, whereas Nvidia Corp. is coded 1 in the same year. To avoid biased estimates we impute missing values for *Market value* and employees (and calculate *Capital intensity* on the basis of the imputed variables).

3.3 Control variables

In the models that we present below, we also include a dummy variable that captures whether a company had any foreign sales in the year of analysis. Data come from Worldscope, with missing values multiply imputed. For the year 2016, our data indicate that 56 percent of the firms in our sample had no foreign sales. Moreover, we include sector, year, and weekday and in models 1 and 2 also agreement fixed effects. Doing so controls for heterogeneity across industry sectors, time, weekdays (where Sunday announcements might be different to, for example, Tuesday events), and agreement. The sector fixed effects are at the top level of the Standard Industrial Classification. At this level, we distinguish 9 industry sectors, such as "agriculture, forestry and fishing" and "services".

3.4 Estimation

The model that we estimated hence is:

$$
\begin{aligned}
CAR_{i,T} = & \gamma_1 Progress_T + \gamma_2 Size_{i,T} + \gamma_3 Capitalintensity_{i,T} + \gamma_4 Diversification_{i,T} + \\
& \gamma_5 Progress_T * Size_{i,T} + \gamma_6 Progress_T * Capitalintensity_{i,T} + \\
& \gamma_7 Progress_T * Diversificiation_{i,T} + \\
& \gamma_8 Sector_i + \gamma_9 Year_T + \gamma_{10} Weekday_T + \gamma_{11} Agreement,
\end{aligned} \tag{1}
$$

where i refers to a specific firm and T to a specific event. We estimate this model relying on ordinary least squares regression, but using the method of alternating projections to get rid of multiple group effects. We also cluster standard errors by firm to account for correlations across events.

Despite the control variables included in our models, we face the problem (common to all event studies) of ascertaining that the abnormal returns that we establish are really caused by the events that we single out and not other information that investors receive. For example, also news about the presidential campaign in the United States during 2016 had an impact on the stock market returns of companies (Wolfers and Zitzewitz, 2018). We offer three responses to this concern. First, we have a relatively large number of both positive and negative events. The probability that other, random events are driving our results declines as the number of events that we study increases. Second, we are testing interactions between events and firm characteristics. Other events that matter for stock prices thus only are a concern if they also matter conditionally in the same way we hypothesize the trade negotiation news to matter. Third, in robustness checks we present models for which we re-estimate our models for randomly chosen dates. If we do not find the same associations as for our event dates, the plausibility of the conclusion that our event dates actually capture a real effect increases.

4 Findings

We present the results from five models in Table 3. The first model only contains main effects, without interaction terms. We find an overall negative effect of the *Progress* variable. This confirms the tentative finding in the descriptives (see Figure 2). On average, US companies thus lost from progress in the negotiations over trade agreements.[13] Interestingly, the two agreements vary with regard to the overall effect of negotiation progress (see Model 2). Whereas progress in TPP negotiations results in an overall drop in stock returns, progess in TTIP negotiations leads to a gain in stock market returns. With respect to the other main effects, capital intensive companies had greater losses than other companies, whereas diversified companies experienced greater gains.

Yet, models 3 to 6 are more meaningful as they test our hypotheses and might explain why we see a negative effect of the *Progress* variable in model 1. In Model 3, we add three interaction terms. The coefficient for the *Progress* × *Market value* term is negative and statistically significant. This is in line with H1. As our dataset excludes small companies that are not listed on the stock market, this result suggests that medium-sized companies benefit dis-proportionally more from progress in TTIP and TPP negotiations than large companies. Figure 3 supports

[13] This result holds even if we delete the extrem TTIP event of 9 November 2016. See Table 1 in the Appendix.

	All				TTIP	TPP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Progress	−0.00***	−0.01***	−0.00	−0.00	−0.00	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market value (log)	−0.00	−0.00	0.00***	0.00***	0.00***	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital intensity	−0.00*	−0.00*	−0.00**	−0.00**	−0.00	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Diversification	0.00***	0.00***	−0.00	−0.00	−0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign sales (dummy)	−0.00	−0.00		0.00	0.00	−0.00
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
TTIP		0.01***				
		(0.00)				
Progress x TTIP		0.01***				
		(0.00)				
Progress x Market value (log)			−0.00***	−0.00***	−0.00*	−0.00**
			(0.00)	(0.00)	(0.00)	(0.00)
Progress x Capital intensity			0.00	0.00	0.00	0.00
			(0.00)	(0.00)	(0.00)	(0.00)
Progress x Diversification			0.00**	0.00**	0.00*	0.00*
			(0.00)	(0.00)	(0.00)	(0.00)
Market value x Foreign sales				−0.00	−0.00	0.00
				(0.00)	(0.00)	(0.00)
Progress x Foreign sales				−0.00	0.00	−0.00
				(0.00)	(0.00)	(0.00)
Progress x Market value x Foreign sales				−0.00	−0.00	0.00
				(0.00)	(0.00)	(0.00)
Num. obs.	68537	68537	68537	68537	35002	33535
R^2 (full model)	0.07	0.07	0.07	0.07	0.09	0.10
R^2 (proj model)	0.01	0.04	0.01	0.01	0.00	0.03
Adj. R^2 (full model)	0.07	0.07	0.07	0.07	0.09	0.10
Adj. R^2 (proj model)	0.01	0.04	0.01	0.01	0.00	0.02

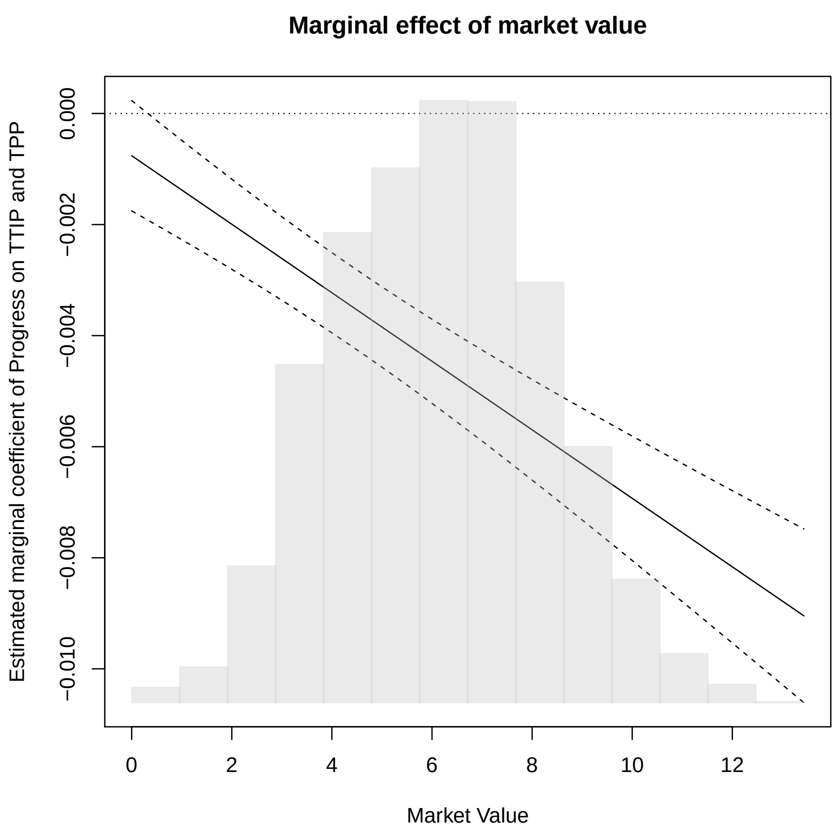
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3: Baseline models

this finding. The larger a company, the less it benefits from positive news on TTIP and TPP. In fact, a company with a market value of $127 million experiences on average a 0.74 percent higher increase of its stock market value than a company with a market value of $2,651 million.[14]

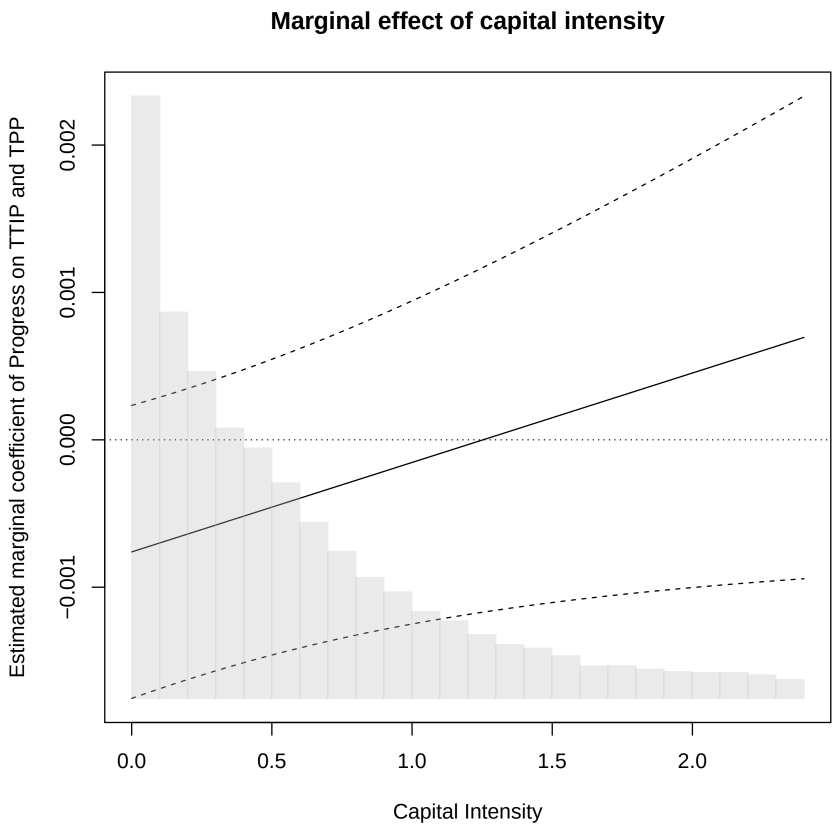
[14] These values reflect the first and the third quartile of market value in our dataset.

Figure 3: The interaction between *Progress* and *Market value*



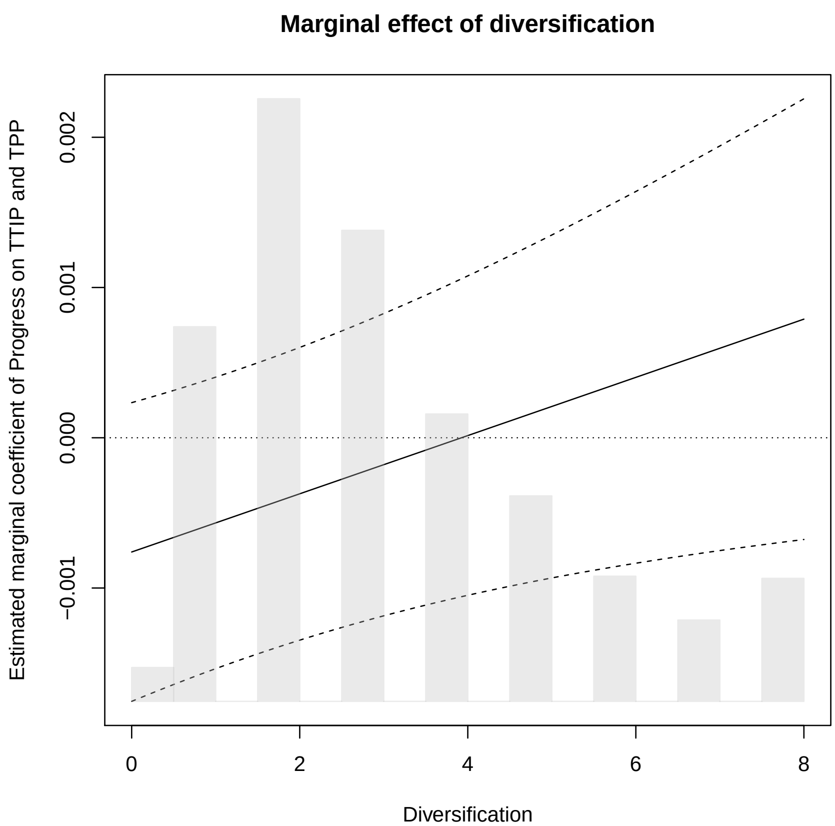
Hypothesis 2 suggests that capital-intensive firms profit more from an advancement in trade negotiations than labor-intensive firms. In Model 3, the coefficient for the interaction between *Progress* and *Capital intensity* is positive, but fails to meet the required significance level. Figure 4 shows this effect graphically. Hence, hypothesis 2 cannot be confirmed.

Figure 4: The interaction between *Progress* and *Capital intensity*



Moreover, in Model 3 we take up the expectation that news that trade negotiations are progressing well are particularly beneficial for the stock market value of diversified companies. As expected in H3, the coefficient for the interaction term is positive and statistically significant. However, Figure 5 shows that this effect is not statistically significant. Also, the substantive effects are quite small: With one additional operating sector a company wins 0.001 in cumulative abnormal returns.

Figure 5: The interaction between positive event and diversification



We further explore the effect of *Market value* in Model 4, where we add a triple interaction term covering *Progress*, *Market value*, and *Foreign sales*. The expectation that we presented in the argument is that especially medium-sized companies that did not yet export benefit most from a trade agreement. This is so as moving from non-exporting to exporting status comes with the highest growth opportunities. This should be less pronounced for large companies that can afford export expansion in the absence of trade agreements. Indeed, the coefficient of *Progress x Market value*, that represents large companies with no sales, is negative and significant. This means that large companies with no foreign sales loose more than medium sized companies that also lack sales. In other words, size does not matter in the presence of foreign sales, but makes a difference for firms with larger export opportunities. Medium-sized firms with no foreign sales seem to be the main winners of progress in trade agreements.

Next, in Model 5 we replicate Model 4, but only for events related to TTIP. Model 6, in contrast, refers solely to TPP events. The direction of the effects are generally the same in the two models. This suggests that the same mechanisms are at work for TTIP and TPP: large non-exporters loose, medium-sized domestic firms as well as diversified firms gain. Yet, Figures 6, 7, and 8 show that the effects are more pronounced for TTIP than TPP. In general, and also visible in Model 2, progress in TTIP seems to generate less stock market losses than progress in TPP.

Figure 6: The interaction between *Progress* and *Market value* (TPP on the left and TTIP on the right)

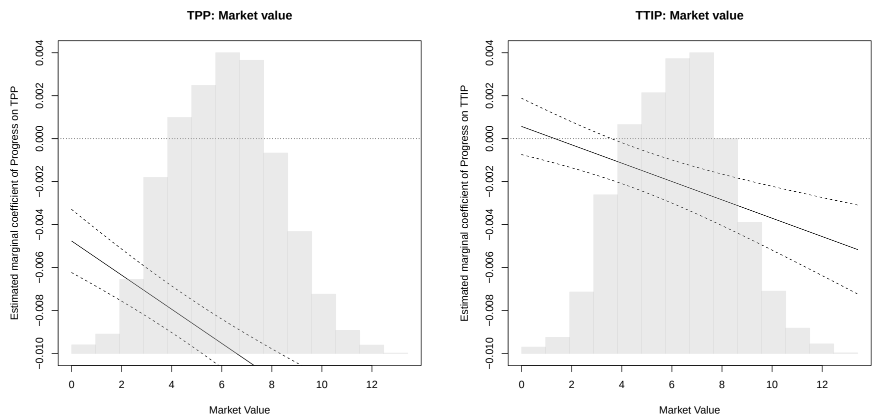


Figure 7: The interaction between *Progress* and *Capital intensity* (TPP on the left and TTIP on the right)

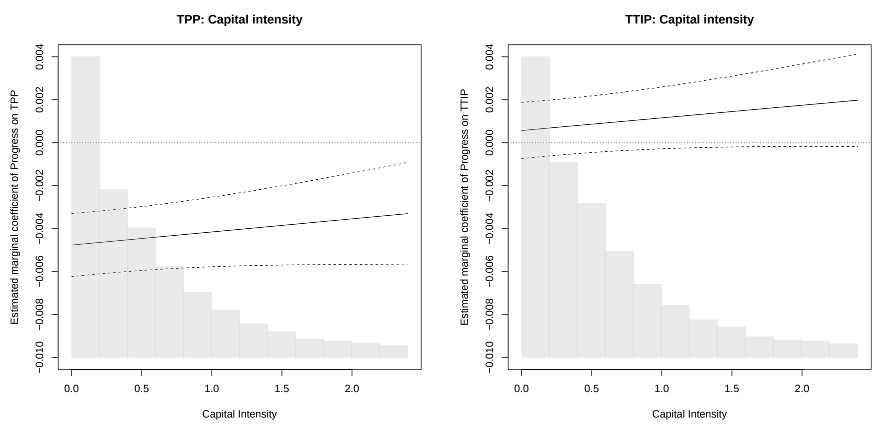
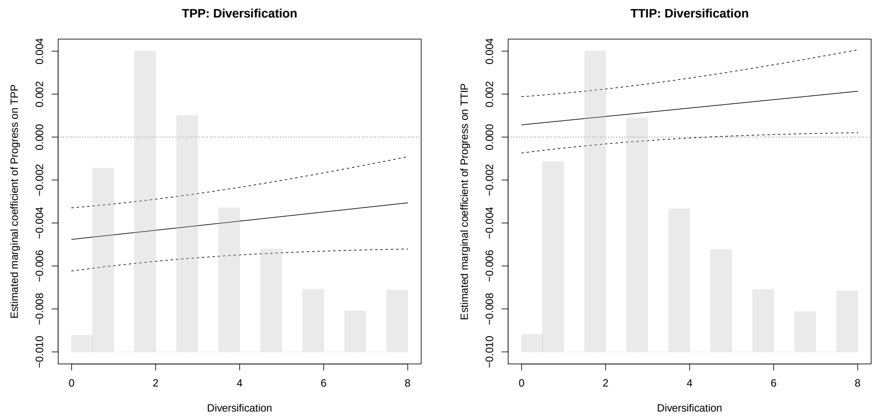
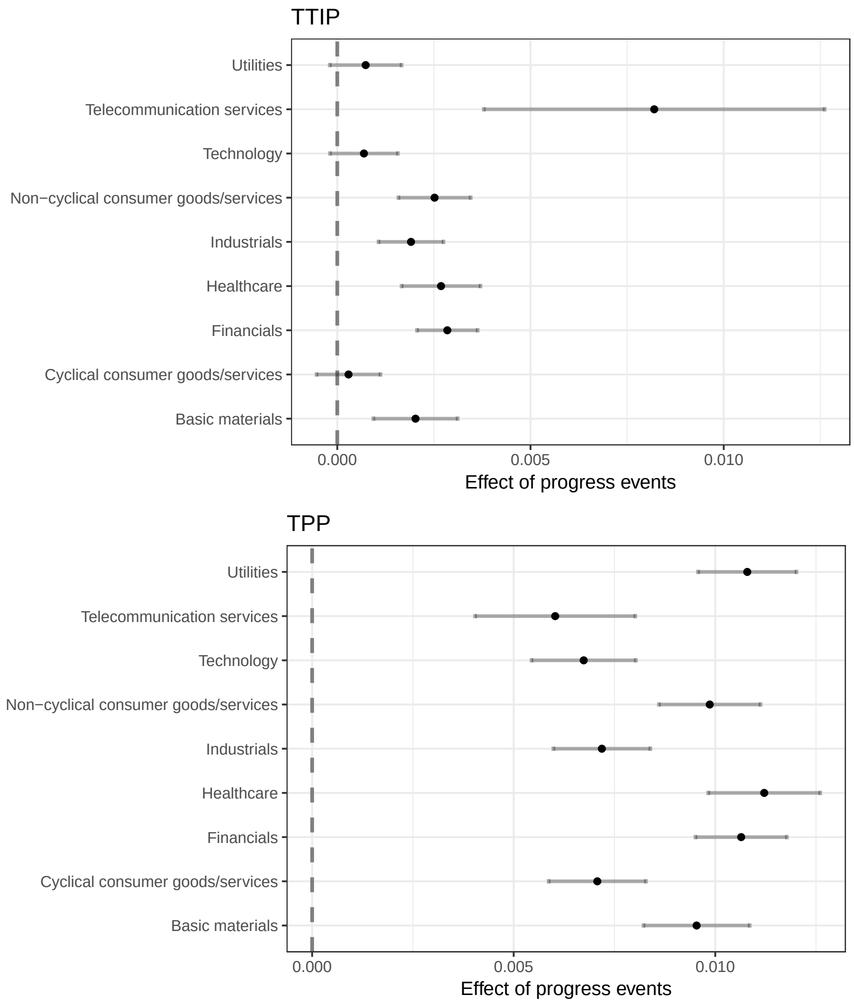


Figure 8: The interaction between *Progress* and *Diversification* (TPP on the left and TTIP on the right)



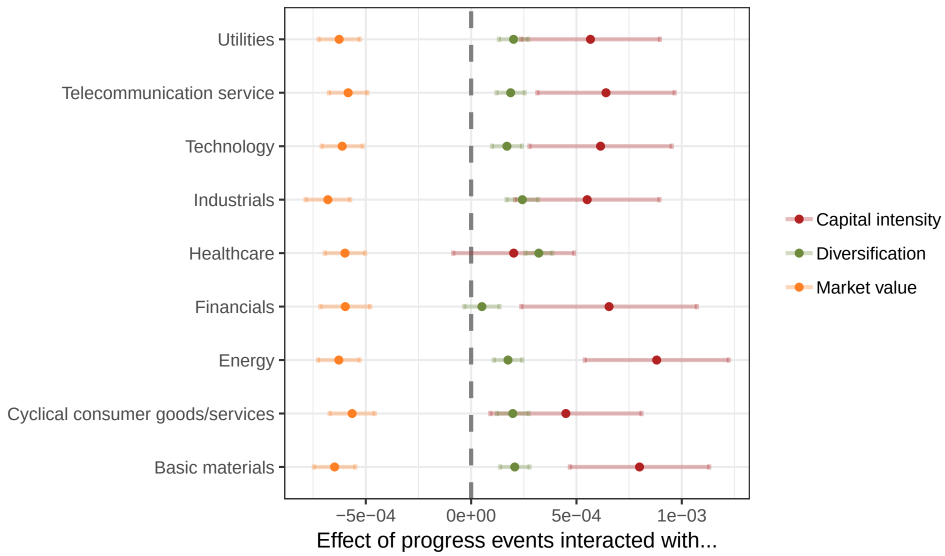
We are also interested in assessing variation in effects across sectors. With the energy sector as the baseline category, Figure 9 shows that especially the telecommunication services sector gained when TTIP negotiations progressed. Also the financial services, the healthcare, the consumer goods and services, the industrial, and basic material sectors belong to the winners of TTIP-related progress events. The results on TPP events suggests that the average firm in all sectors benefited relative to the energy sector from advancements in the negotiations. Among the largest winners were companies in the utilities, the healthcare, the consumer goods and services, and the financial services sectors.

Figure 9: Sectoral effects of progress in TTIP and TPP negotiations



With regard to interaction effects, Figure 10 shows that the differences across sectors are relatively small. Large companies in all sectors lose in case of progress events. *Diversification* is significant and positive in all industries, but the financial sector. Capital intensity comes with the largest standard errors. This coefficient is highest for companies in the energy sector and lowest for firms in the healthcare sector.

Figure 10: Sectoral effects of progress events

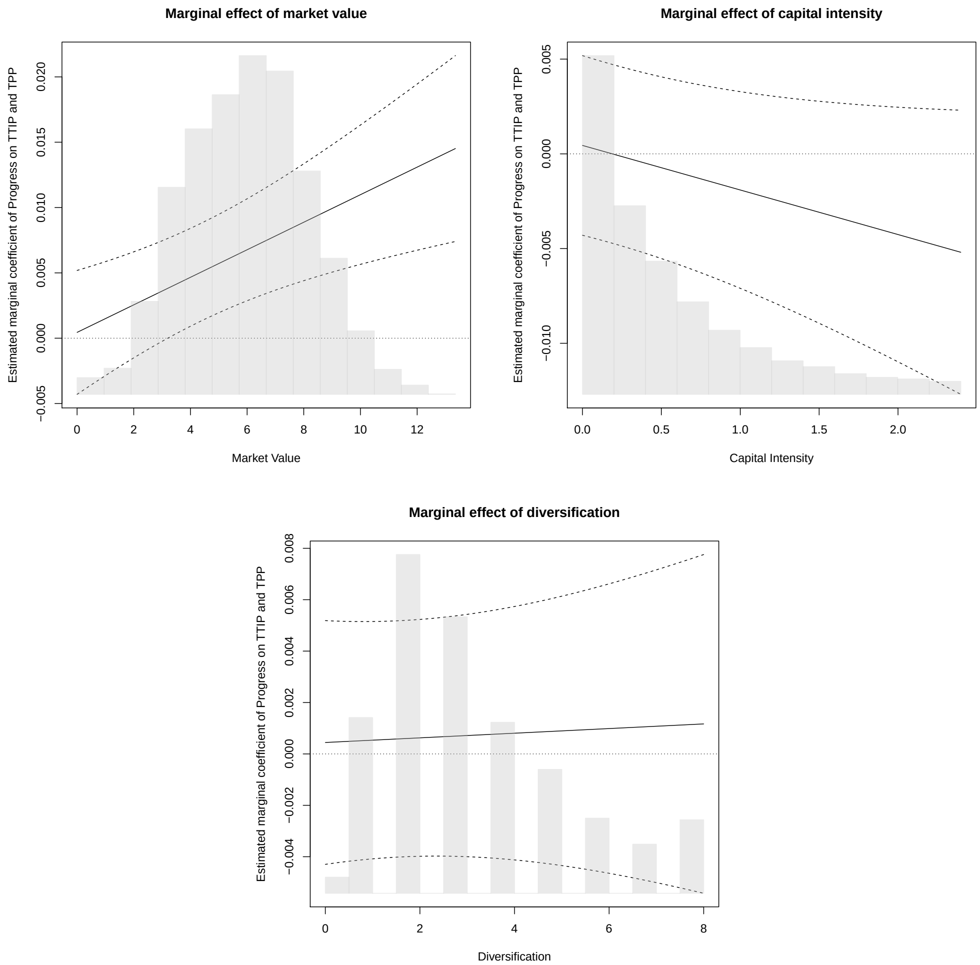


We conducted several robustness checks to see to which extent our findings are driven by specific decisions in terms of operationalization. First, we calculated our dependent variable using the two alternative metrics that we presented in the research design section: an out-of-sample market adjusted model and a mean return model. Second, we varied the length of the event window for which we calculate the cumulative abnormal returns. Instead of a 5 day window, we used a 3 and a 1 day window. Third, we dropped all firms that are not listed on any stock market in the United States.[15] Fourth, we dropped the 9 November 2016 event, which caused significant reactions by more than 1300 firms in the sample, and hence may be driving our results. For all of these tests, the results are similar to those presented above.

Lastly, we ran a placebo test with 15 random events, where we could not find support for our hypotheses (See Figure 11). The interaction between a firm's size and the progress dummy is statistically significant, but positive. On trading dates without event related to TPP or TTIP, therefore, larger firms won more than smaller firms. This result is plausible. The interactions between the progress dummy and *Capital intensity* and *Diversification*, respectively, are not statistically significant. These results make it more plausible that our results above are really related to the TPP and TTIP negotiations.

[15] The full sample consists of firms that have their headquarters in the United States. A minority of these firms are not listed on any US-based stock market.

Figure 11: Placebo Test



5 Conclusion

Discussions over trade agreements circle around the question of their distributional consequences: Who gains and who loses from them? Do large companies gain more than small ones? Are diversified firms better off than firms with a narrow product range?

To answer these questions, we have assessed how the stock prices of United States companies reacted to news on the progress and stagnation of trade negotiations. A dataset on 3,926 companies and their characteristics allowed us to investigate factors that explain varying reactions to news on progress, and as the case may be stagnation, of trade talks. Our empirical analysis focuses on negotiations over TPP and TTIP. These are ideal cases to study, as plenty of ups and downs characterize the negotiations over both agreements.

The central finding is much variation in the effects of the negotiations on the stock prices of companies even when controlling for the sector in which they are active. Our analysis suggests that especially medium-sized companies (that did not yet engage in exports) were expected to gain from the two agreement. The effects that we find for capital intensity and diversification are relatively small.

Overall, the findings of this paper suggest that sectoral models of trade policy-making are no longer sufficient to explain the impact of trade agreements. This should matter for analyses of trade preferences, both of firms and individuals. At the individual level, citizens should not only differ in their preferences towards trade agreements depending on their skill levels or the sector in which they are employed, but also depending on the firm by which they are employed. More specifically, our results indicate that there are winners and losers from trade, but that trade agreements may actually broaden the set of winners as compared to a situation in which trade is already quite liberal, but some important barriers to trade remain.

References

Antràs, P. and Staiger, R. (2012). Offshoring and the Role of Trade Agreements. *American Economic Review*, 102(7):3140–3183. 5

Armstrong, C. S., Barth, M. E., Jagolinzer, A. D., and Riedl, E. J. (2010). Market Reaction to the Adoption of IFRS in Europe. *The Accounting Review*, 85(1):31–61. 3

Baccini, L., Pinto, P., and Weymouth, S. (2017). The distributional consequences of preferential trade liberalization: a firm-level analysis: forthcoming. *International Organization*. 2, 3, 5

Bechtel, M. M. and Schneider, G. (2010). Eliciting Substance from ‚ÄòHot Air': Financial Market Responses to EU Summit Decisions on European Defense. *International Organization*, 64(02):199. 3

Bernard, A., Eaton, J., Jenson, J. B., and Kortum, S. (2003). Plants and Productivity in International Trade. *American Economic Review*, 93(4):1268–1290. 6

Bernard, A. B. and Jensen, J. B. (2007). Firms in international trade. *Journal of Economic Perspectives*, 21(3):105–30. 4, 5

Breinlich, H. (2014). Heterogeneous firm-level responses to trade liberalization: A test using stock price reactions. *Journal of International Economics*, 93(2):270–285. 2, 3, 5

Brown, S. J. and Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, 8(3):205–258. 8

Brown, S. J. and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1):3–31. 8

Burscher, B., Odijk, D., Vliegenthart, R., de Rijke, M., and de Vreese, C. H. (2014). Teaching the Computer to Code Frames in News: Comparing Two Supervised Machine Learning Approaches to Frame Analysis. *Communication Methods and Measures*, 8(3):190–206. 11

Ciuriak, D., Lapham, B., Wolfe, R., Collins-Williams, T., and Curtis, J. (2015). Firms in International Trade: Trade Policy Implications of the New New Trade Theory. *Global Policy*, 6(2):130–140. 2, 3, 6

Davies, R. B. and Studnicka, Z. (2018). The heterogeneous impact of Brexit: Early indications from the FTSE. *European Economic Review*, 110:1–17. 2, 8

Dür, A. (2010). *Protection for Exporters: Power and Discrimination in Transatlantic Trade Relations, 1930-2010*. Cornell University Press, Ithaca, 1. edition. 3

Dür, A., Baccini, L., and Elsig, M. (2014). The design of international trade agreements: Introducing a new dataset. *Review of International Organizations*, 9(3):353–375. 4

European Commission (2013). Impact Assessment Report on the future of EU-US trade relations. Technical report, EU. 6

Gibbons, C., Richards, S., Valderas, J. M., and Campbell, J. (2017). Supervised Machine Learning Algorithms Can Classify Open-Text Feedback of Doctor Performance With Human-Level Accuracy. *Journal of Medical Internet Research*, 19(3). 11

Gilligan, M. J. (1997). *Empowering exporters: reciprocity, delegation, and collective action in American trade policy*. University of Michigan Press. 3

Grimmer, J. and Stewart, B. M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3):1–31. 11

Grossman, G., Levinsohn, J., Grossman, G., and Levinsohn, J. (1989). Import Competition and the Stock Market Return to Capital. *American Economic Review*, 79(5):1065–87. 3

Haselmayer, M. and Jenny, M. (2017). Sentiment analysis of political communication: combining a dictionary approach with crowdcoding. *Quality & Quantity*, 51(6):2623–2646. 10

Helpman, E., Melitz, M. J., and Yeaple, S. R. (2004). Export versus FDI with Heterogeneous Firms. 5

Hiscox, M. J. (2001). Class Versus Industry Cleavages: Inter-Industry Factor Mobility and the Politics of Trade. *International Organization*, 55(1):1–46. 3

Jensen, J. B., Quinn, D. P., and Weymouth, S. (2015). The Influence of Firm Global Supply Chains and Foreign Currency Undervaluations on US Trade Disputes. *International Organization*, 69(04):913–947. 3

Kananovich, V. (2018). Framing the Taxation-Democratization Link: An Automated Content Analysis of Cross-National Newspaper Data. *The International Journal of Press/Politics*, page 194016121877189. 11

Kasahara, H., Lapham, B., Kasahara, H., and Lapham, B. (2013). *Journal of international economics.*, volume 89. North-Holland. 6

Krippendorff, K. (2013). *Content analysis: an introduction to its methodology*. SAGE. 10

Lileeva, A. and Trefler, D. (2010). Improved Access to Foreign Markets Raises Plant-Level Productivity… for Some Plants. *Quarterly Journal of Economics*, 125(3):1051–1099. 6

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(3):13–39. 8

Matsuyama, K. (2007). Beyond Icebergs: Towards a Theory of Biased Globalization. *The Review of Economic Studies*, 74(1):237–253. 6

Melitz, M. J. and Redding, S. (2014). Heterogeneous Firms and Trade. In Gopinath, G., Helpman, E., and Rogoff, K. S., editors, *Handbook of International Economics*, pages 1–54. Elesivier, Oxford. 2, 3, 5

Milner, H. V. (1988). *Resisting protectionism : global industries and the politics of international trade*. Princeton University Press. 3

Monroe, B. L. and Schrodt, P. A. (2008). Introduction to the Special Issue: The Statistical Analysis of Political Text. *Political Analysis*, 16(04):351–355. 3

Moser, C. and Rose, A. K. (2014). Who benefits from regional trade agreements? The view from the stock market. *European Economic Review*, 68:31–47. 2

Osgood, I. (2017). The Breakdown of Industrial Opposition to Trade. *World Politics*, 69(01):184–231. 3

Osgood, I. (2018). Globalizing the Supply Chain: Firm and Industrial Support for US Trade Agreements. *International Organization*, pages 1–30. 3

Parinduri, R. A. and Thangavelu, S. M. (2013). Trade liberalization, free trade agreements, and the value of firms: Stock market evidence from Singapore. *The Journal of International Trade & Economic Development*, 22(6):924–941. 2

Persin, D. (2011). Market Access for Small Versus Large Service Enterprises: The Preferential and Multilateral Trade Liberalization Tracks Compared. *Journal of World Trade*, 45(4). 6

Porter, M. F. (1980). An algorithm for suffix stripping. *Program*, 14(3):130–137. 11

Rodriguez, P. (2003). Investor Expectations and the North American Free Trade Agreement. *Review of International Economics*, 11(1):206–218. 2, 3

Rodrik, D. (2018). Populism and the economics of globalization. *Journal of International Business Policy*, 1(1-2):12–33. 2

Saval, N. (2017). Globalisation: the rise and fall of an idea that swept the world — World news — The Guardian. 2

Schmid, H. and Schmid, H. (1994). Probabilistic Part-of-Speech Tagging Using Decision Trees. 11

Schneider, G. and Troeger, V. E. (2006). War and the World Economy. *Journal of Conflict Resolution*, 50(5):623–645. 3

Thompson, A. J. (1993). The Anticipated Sectoral Impact of the Canada-United States Free Trade Agreement: An Event Study Analysis. *Canadian Journal of Economics*, 26:253–271. 2

Thompson, A. J. (1994). Trade liberalization, comparative advantage, and scale economies stock market evidence from Canada. *Journal of International Economics*, 37(1-2):1–27. 2

Wagner, J. (2012). International trade and firm performance: a survey of empirical studies since 2006. *Review of World Economics*, 148(2):235–267. 6

Wilkerson, J. and Casas, A. (2017). Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges. *Annual Review of Political Science*, 20(1):529–544. 3

Wolfers, J. and Zitzewitz, E. (2018). The Standard Error of Event Studies: Lessons from the 2016 Election. *AEA Papers and Proceedings*, 108:584–89. 3, 4, 16

Workman, G. (2014). The Transatlantic Trade and Investment Partnership: Big Opportunities for Small Business. 2, 6

World Trade Organization (2008). World trade report: trade in a globalizing world. Technical report, WTO, Geneva. 4