

Trump, Tariffs, and Tweets: How Trade Negotiations and Presidential Communication Impact Auto Manufacturers

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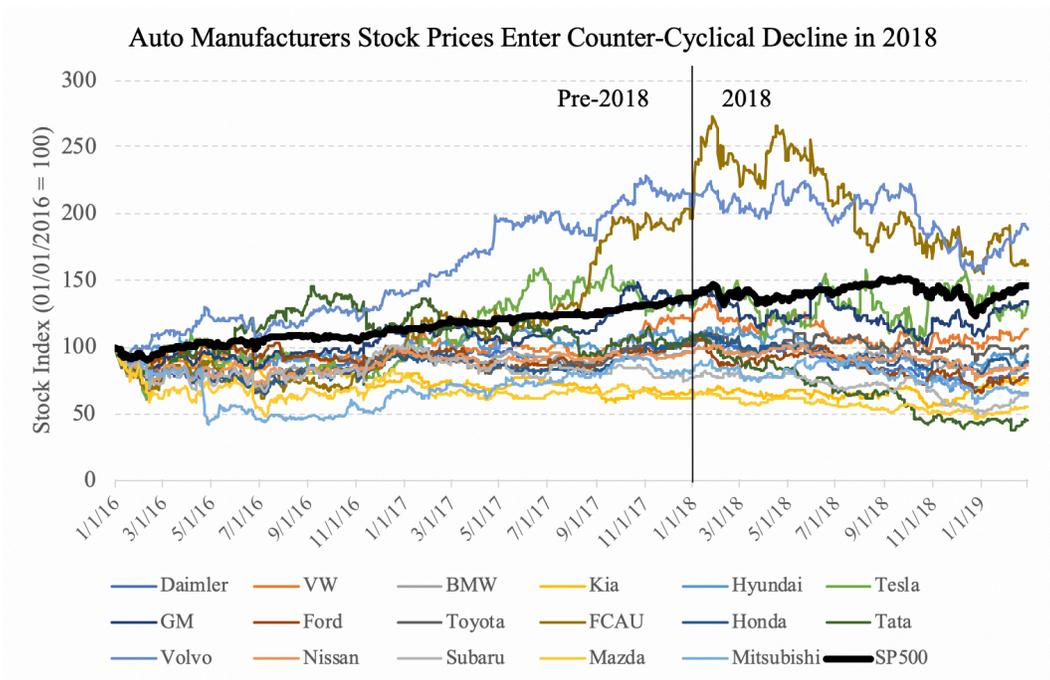
Abstract

One of President Trump's election promises was that he would put "America First" by renegotiating trade deals to be more favorable for U.S. businesses. Of particular importance to President Trump was the U.S. auto manufacturing industry. My thesis evaluates if the Trump Administration has achieved this goal throughout the 2017-2018 trade negotiations by using stock prices to proxy for firm health. I first read and categorize WSJ articles and President Trump's tweets to create datasets that identify days of increasing and decreasing trade negotiation tensions. Using these datasets, along with firm-level production data, I show that the trade negotiations have incentivized firms to shift production to the U.S., albeit with varying degrees of effectiveness. Additionally, I report that President Trump's tweets impact auto manufacturers in a significant manner, even causing European auto manufacturers to underperform non-European auto manufacturers by 0.535% following tweets that increase NAFTA tensions. These results vary with the WSJ and Tweet datasets, demonstrating the salience of direct presidential communication.

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I. Preliminaries

One of President Trump’s election promises was that he would put “America First” by renegotiating trade deals to be more favorable for U.S. businesses. Of particular importance to President Trump was the U.S. auto manufacturing industry. To achieve this “America First” policy goal, President Trump has engaged in trade negotiations with China and NAFTA and has had more broad trade negotiations concerning auto tariffs as well as Steel and Aluminum tariffs throughout 2017-19. My thesis evaluates how the Trump Administration has impacted auto manufacturers via each of these trade negotiations by using stock prices to proxy for firm health. Below, I illustrate that the stock prices of 17 large auto manufacturers entered a counter-cyclical decline since the start of 2018, which coincides with the start of several U.S. trade negotiations. Although this suggests that trade negotiations have harmed auto manufacturers, including U.S. auto manufacturers, it does not prove the causal link between increased trade tensions and worse stock performance. To provide conclusive evidence that trade negotiations have impacted auto manufacturers, I must determine that stock prices behave consistently on trade negotiation days.



A. The Research Question

Stock prices reflect market expectations regarding future profits and, thus, can capture the impact of news events on firm health. However, stock prices do not capture the impacts of trade negotiations on the U.S. auto manufacturing labor market. A particular trade deal could cause firms to shift more of their supply chains to the U.S., thereby inducing medium-term costs. By shifting production to the U.S., these firms increase employment within the U.S. auto manufacturing sector. While my analysis is useful in evaluating how the trade negotiations have impacted auto manufacturers, it falls short of providing a comprehensive picture of the impacts on U.S. auto manufacturing labor markets.

To more accurately gauge the impact of trade negotiations on auto manufacturing stock prices, I classify the trade negotiations into four trade categories: 1) section 301 tariffs with China 2) NAFTA renegotiations 3) potential section 232 tariffs on automobiles and parts and 4) section 232 tariffs on steel and aluminum. Since each trade category places tariffs on different goods and each firm has its own complex supply chain, each trade category should have a unique impact on each firm. For instance, a US-based firm might benefit from tariffs on imported autos, but be harmed by tariffs on imported steel and aluminum. In Section II, I provide a more in-depth background on each of these trade categories.

To identify trade negotiation events, I create two datasets: one based on Wall Street Journal articles and another based on President Trump's Tweets. Each dataset records if trade events occurred on a given date, which categories were subject to these events, and if these events increased, decreased, or had an ambiguous impact on trade negotiation tensions. By regressing this tension variable against stock price returns, I am able to measure the impact of trade tensions on stock prices. Additionally, I collect firm-level supply chain data in order to test

the impacts of trade negotiations on different types of firms. Most importantly, this firm-level data delineates between firms with high and low U.S. production and, thus, allows me to test if the trade negotiations have caused high U.S. production firms to outperform low U.S. production firms.

B. Literature Review

My research on trade negotiations pertains to three strands in the literature: 1) the implications of uncertainty on firms, 2) the implications of trade policy on firms, and 3) the implications of trade policy specifically for the auto-manufacturing industry. When the Trump Administration enters in trade negotiations, the outcome of these negotiations is uncertain. The literature on uncertainty and firm decision-making can be traced back to Bernanke (1983), which determines that firms should hire or invest immediately only if the cost of holding out on investment outweighs the benefit of waiting for more information. This research is furthered by Bertola and Cabellero (1994), which show that volatile firm-level decisions can be smoothed to produce a macro-economic effect. Additionally, Abel and Eberly (1996) add nuance to the cost of reversing an investment decision. Clearly, auto-manufactures would benefit from holding off decisions until the tariff negotiations have finished.

On an empirical front, this strand of literature has focused on either measuring general uncertainty shocks, like 9/11, or policy uncertainty shocks, like debates regarding the debt ceiling. Romer (1990) and Bloom (2009) use stock market volatility to proxy for uncertainty and demonstrate that uncertainty shocks have detrimental impacts on macro-level indicators such as production and employment. More recently, Bloom et al. (2018) and Bachmann, Elstner, and Sims (2013) use firm-level productivity and forecast surveys, respectively, to quantify the

harmful impact of uncertainty shocks. Born and Pfeifer (2014) and Villaverde et al. (2015) demonstrate the same harmful effect, but focus on fiscal policy uncertainty. Yet, while other research has shown that uncertainty can have large consequences, Villaverde et al. (2015) finds that a two standard deviation shock to policy risk only decreases production by 0.065%. To this literature, my research offers a case-study of a policy uncertainty shock and its implications for firm-level stock movements.

My research also pertains to the implications that proposed tariffs have on the auto-manufacturing industry. The impacts of trade policy on a specific firm can be complex as firms might find it more beneficial to overcome tariffs by producing locally in the foreign country. Cole and Davies (2011) build a theoretical model demonstrating that a firm might decide to pay the tariff up till a certain rate, after which it decides to produce locally. Empirically, Hanson, Mataloni, and Slaughter (2001) and Helpman, Melitz, and Yeaple (2004) use data on multinational firms to support this theoretical result. This line of research is especially relevant to the auto-industry because many firms have decided to build plants within the United States, and these firms will not face the full force of proposed tariffs. Yet, even domestically producing firms are not immune to the negative impacts of tariffs, as many domestic plants rely on imported intermediate inputs. By distinguishing between domestic and foreign firms, my research offers a case-study of the potential impact of increased tariffs on firms with high domestic production versus firms with low domestic production.

Lastly, my research pertains to the sparse literature specifically concerning the impacts that tariffs have had on the auto-manufacturing industry. Goldberg (1995) constructs a model of the U.S. automobile industry by calibrating a nested discrete choice model using 1983-1987 microdata from the Consumer Expenditure Survey and concludes that, in response to auto tariffs,

consumers would first switch to other foreign models before switching to a domestic model. This suggests that automobile tariffs would have to be substantial to benefit domestic manufacturers.

My research most directly pertains to three strands of literature: 1) the impacts of uncertainty, 2) the impacts of trade policy on industries and, 3) the impacts of tariff policy on specifically the auto-manufacturing industry. While my research fills gaps in each of these strands, my research is primarily concerned with how these three distinct strands interact with one another. By analyzing a case-study of the stock price implications of tariff negotiations, my research assesses if the negotiation of proposed tariffs generates enough uncertainty and shifts in expected profits to have a measurable impact on stock price returns. By identifying Wall Street Journal articles and President Trump's tweets regarding trade negotiations, I follow a similar procedure as Baker, Bloom, and Davis (2016) and demonstrate its effectiveness for future research.

C. Roadmap

Section II provides a background on the trade negotiations. Section III describes the collected Wall Street Journal and Tweet datasets. Section IV describes the firm-level data. Section V reports the regression results and relates them to the Trump Administration's stated policy goals. Section VI concludes and outlines further lines of research.

II. Description of the Trade Negotiations

To provide context for the upcoming analysis, I first provide background information regarding the various trade negotiation categories that have occurred over 2017 and 2018.

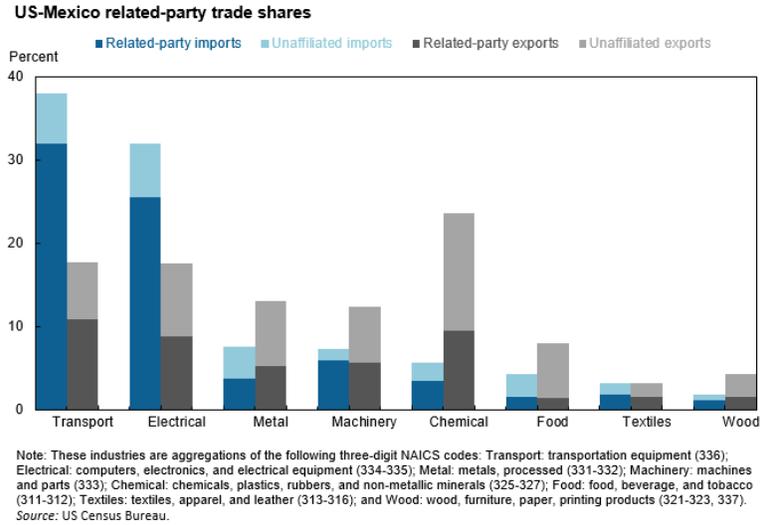
Section 301 China:

The section 301 tariffs follow an investigation into China's forced technology transfer and its unfair trade policies and practices (United States, Congress, Office of the United States Trade Representative). Over the course of two rounds of tariffs, China has placed a 5-25% tariff on roughly \$110 billion U.S. exports, including a 25% tariff on the \$10 billion automobiles that the U.S. exports to China (Bown, "More than Soybeans"). Additionally, the U.S. placed a 10% tariff on roughly \$250 billion dollars of Chinese imports, including \$15.6 billion automobile parts (Bown et al. "Trump and China"). Moreover, on June 27th, the U.S. Secretary of the Treasury, Steven Mnuchin, claimed that the U.S. can block American joint ventures from engaging in technology transfer with their Chinese counterparts (Chorzempa and Hufbauer). Several auto-manufacturers, including Ford, General Motors and Fiat Chrysler, form joint ventures with Chinese companies in order to avoid the steep 25% tariff that China places on imported vehicles. Thus, the section 301 tariff negotiations should impact auto manufacturers that produce in the United States and export vehicles to China, U.S. auto manufacturers that rely on Chinese automobile parts, and U.S. auto manufacturers with Chinese joint ventures.

NAFTA:

NAFTA is a free trade agreement between the U.S., Canada, and Mexico, causing many manufacturers to treat the entire North American continent as one supply chain entity. The image below demonstrates that the NAFTA region has a high percentage of related-party imports and exports, i.e. when a company exports intermediate goods from the U.S. to Mexico. Of the \$88.5 billion U.S. exports in automobile parts, roughly \$63 billion are destined for Canada or Mexico, and of the \$159 billion U.S. imports of automobile parts, roughly \$77 billion are from Mexico or Canada (Robinson et al.). Additionally, over \$90 billion of U.S. automobile imports are from

NAFTA and almost \$10 billion of U.S. automobile exports are to NAFTA (ibid.). NAFTA is critical for the auto industry.



(Image from Amiti et al.)

The Trump Administration has engaged in NAFTA trade negotiations in order to incentivize more U.S. production. Before negotiations started, 62.5% of the value of a car had to be of regional production in order to be exempt from tariffs within NAFTA. By increasing this rule of origin to 75%, and ultimately also introducing a new requirement that 40% of the value of a car must be produced by workers earning above \$16 an hour, the USMCA, which is the revised NAFTA, serves to increase costs for auto manufacturers looking to benefit from NAFTA’s free trade region (Hufbauer). While manufacturers that rely heavily on Canada and Mexico are hurt, they are also incentivized to shift more production to the U.S. Due to the magnitude of these imports and exports, stricter requirements are expected to have a large impact on auto manufacturers that produce in multiple NAFTA countries.

If auto manufacturers decide to not comply with NAFTA, they will face the Most Favored Nation (MFN) tariffs, which are rather small at 2.5% for cars. In order to incentivize firms to comply with the stricter NAFTA requirements rather than pay this MFN tariff, it is

expected that these MFN tariffs will be increased, hurting all manufacturers that import cars into the U.S. (Schott).

Section 232 Autos and Automobile Parts:

President Trump initiated a section 232 National Security Investigation into automobiles and automobile parts on May 23, 2018, following trade negotiations with the European Union concerning Steel and Aluminum tariffs. If autos are found to be a national security threat, then all auto-manufacturers that either import automobiles into the U.S. or use imported automobile parts in U.S. productions would be impacted. However, it is important to note that the NAFTA-complying models would be exempted. While this national security investigation was not due to finish before 2019, President Trump has tweeted multiple times concerning the unfair auto trade between the United States and the European Union in 2018. In table 1, I have tabulated the relevant imports by country. Since NAFTA complying vehicles are exempt, the most afflicted trading partners are the EU and Japan, which import \$46.6 and \$43.3 billion passenger cars into the U.S.

Table 1: U.S. Vehicle Imports by Trade Partner

<u>US Car Imports in Billions</u>		<u>US Truck Imports in Billions</u>	
Country	Amount	Country	Amount
EU28	46.6	Mexico	22.8
Canada	43.3	Canada	1.4
Japan	43	EU28	1.2
Mexico	30.6	Japan	0.8
Korea	15.7	Brazil	0.1
China	1.8	Argentina	0
Rest of world	2.8	Rest of world	0.1
Total	183.8	Total	26.4

(Data from Robinson et al., “Trump's Proposed Auto Tariffs”)

Section 232 Steel and Aluminum:

On February 16, 2018, a U.S. section 232 national security investigation finds that steel and aluminum constitute a threat to national security. In response to the results, on March 1, 2018 President Trump announces a 25% tariff on all steel imports and a 10% tariff on all aluminum imports. In terms of trade volume, Canada and the European Union export by far the most amount of steel and aluminum to the U.S., at \$12 billion and \$7.3 billion respectively (Bown, “Trump’s Steel”). According to the Bureau of Economic Analysis’s 2017 U.S. Input-Output tables and Import Input-Output tables², the U.S. Motor vehicles, bodies and trailers, and parts industry requires a total of \$577.4 billion worth of intermediate goods. Of this \$577.4 billion, roughly \$111 billion are in metals and fabricated metal products, including \$18.1 billion that are imported from abroad. Imported metals and fabricated metals contribute 3.1% to overall intermediate costs for the U.S. auto industry. Thereby a tariff on such imports should impact U.S. auto manufacturers, however these impacts are dwarfed by the NAFTA negotiations.

Vague:

Lastly, the Trump Administration intermittently releases statements that do not relate to an individual trade negotiation, but rather to the trade negotiations generally. Since these statements do not fall cleanly into any one trade category, I create a Vague category containing all such statements.

Discussion:

The most disruptive tariffs would be on all U.S. imports of automobiles, which would seriously harm European and Japanese producers. A close second are the NAFTA negotiations that not only directly harm auto manufacturers with plants in Canada and Mexico, but also auto

² Source: <https://www.bea.gov/industry/input-output-accounts-data>

manufacturers that do not fulfill NAFTA requirements and instead rely on the 2.5% MFN tariff to import cars into the U.S. Lastly, the Chinese trade negotiations and the Steel and Aluminum trade negotiations harm auto manufacturers with a large U.S. presence, although the Chinese trade negotiations also harm U.S. auto manufacturers with Chinese joint-ventures. In comparison, it is hard to estimate the impact of the Vague trade category due to its broad and overarching nature; maybe the statements are seen to impact all trade categories and, thus, have enormous impacts, or maybe the statements are seen as toothless political ploys. By delineating between these various trade categories, my analysis will capture and test these different effects. For brevity, I will refer to the five trade categories mentioned above as China, NAFTA, Cars, Steel, and Vague.

III. Description of News Datasets

I analyze two sources for trade-related news: 1) stated Trump Administration policy goals and the results of concrete events pertaining to the negotiations and 2) President Trump's tweets regarding his personal views of the trade negotiations. To proxy for policy goals and event outcomes, I use the Factiva Database to pull all 3,047 WSJ articles from 2018 that contain the words "tariff" or "tariffs" and proceed to read and classify each of these articles.³ Similarly, I read and classified all of the 6,072 President Trump tweets from 2017 and 2018, collected from the Trump Twitter Archive.⁴ Due to time restrictions, I was unable to extend my WSJ analysis to 2017, which would have included more information regarding NAFTA negotiations. Below I give a brief explanation of the WSJ articles and Tweets.

³ Source: <https://global.factiva.com/sb/default.aspx?lnep=hp>

⁴ Source: <http://www.trumptwitterarchive.com/archive>

A. Comparison between WSJ articles and Tweets

i. Wall Street Journal Articles

The WSJ journal articles follow the timelines for the trade categories very closely; there are articles concerning the outcomes of bilateral negotiations, the threat of tariffs, the retaliatory actions taken in response to tariffs, the statements of multilateral meetings like the G7, the impacts and potential impacts of the trade negotiations on the economy, the lobbying efforts taken to influence the trade negotiation, the efforts Congress has taken to curb the Trump Administration's power over trade negotiations, the disagreements occurring within the Trump Administration with regards to official trade policy, the hiring or firing of Trump Administration personnel, the rhetoric President Trump expresses during his nationwide rallies, and even some of President Trump's tweets. In sum, the WSJ articles cover a wide breadth of events that minutely detail the trade negotiation at every step.

Since the WSJ online publishes articles as soon as possible, I use the published date of a WSJ article to proxy for the date that the event occurred on. While there are opinion pieces regarding many of these events, they almost always follow a WSJ article that provides an unbiased account of the event. Thus, by only considering the non-opinion pieces, I am able to build a dataset that is representative of even minute trade events.

ii. President Trump's Tweets

In contrast, President Trump's Tweets do not cover all of the trade negotiation events. Instead, the president tends to tweet about his personal views on the trade negotiations. Since these vary greatly between the various categories of trade negotiations, I summarize the content of the tweets by category below.

China: They mostly contain descriptions about the previous bad trade deals that were struck and the unfair trade practices that currently occur. Relative to the NAFTA tweets, these tweets are more threatening in nature, explicitly mentioning the trade war, but are not overly hostile.

NAFTA: They mostly contain descriptions about the trade deficit and the unfair trade practices that occur. It is interesting that while the WSJ dataset provides an account of President Trump's willingness to back out of NAFTA trade renegotiations, these are largely absent from President Trump's tweets.

Cars: They almost exclusively threaten automobile tariffs on the EU, but a couple of tweets are aimed at China's auto tariffs on US cars. The tweets explicitly mention a 20% tariff on all automobile imports from Europe if bilateral relations do not improve, and they do not seem to also target Japan, Mexico, or Canada. This is in contrast to the national security investigation, which does not discriminate auto related imports based on country of origin.

Steel and Aluminum: They mostly exclaim the importance of steel and aluminum and the unfair trade practices that occur, especially with the EU. There are some #MAGA and #AmericaFirst tweets that create a sense of nationalism, but without explicit threats.

Vague: These tweets are not explicitly referencing specific events, but rather serve to communicate President Trump's view on the general trade negotiation process. They focus broadly on unfair trade deals, trade deficits, general threats, and vague hashtags like #AmericaFirst and #MAGA.

iii. Pros and Cons of WSJ versus Tweet Datasets

Obviously, the two datasets contain different accounts of the trade negotiations. Since the WSJ dataset captures a broad set of trade events that cover minute events, one could argue that they are more representative of Trump Administration policy as a whole. In comparison, since President Trump personally writes his tweets, the Tweet dataset is perhaps closer to President Trump's thoughts and intentions. This intimacy comes at the cost of breadth; President Trump tweets about the events that he deems to be worthy of a tweet. Thus, it is not a priori clear if one dataset should have larger impacts than the other. By comparing the results of these two datasets, I evaluate the impact of direct presidential communication versus general administrative policies. How salient are President Trump's tweets to investors?

B. Description of the Processed Dataset

In appendix A, I include a step-by-step explanation of my data collection process, including summary statistics of the article and tweet markings. Broadly speaking, I first discard all articles and tweets that do not pertain to the trade negotiations. I then take each of the remaining news events and categorize them into one of the five trade categories: China, NAFTA, Cars, Steel, and Vague. I also classify if the news event seems to illustrate increasing, ambiguous, or decreasing trade tensions. If an article or tweet occurs on a weekend, it gets assigned to the next Monday, since stock exchanges are closed on weekends. Since multiple article or tweets might occur on the same day, I create a news ranking to differentiate between the important and less-important news events and discard those news events with relatively low news ranks for that particular day. If more of remaining news sources indicate that tensions have increased rather than decreased, then the day is marked as a day of increasing trade tensions.

This procedure is replicated across all trade categories and separately for WSJ articles and Tweets; each day gets its own tension assignment for each trade category and for both the WSJ and the Tweet analysis.

i. Tabulations of the Tension Variable

On the next page, in tables 2 and 3, I have included tabulations of the tension variable by trade category for the WSJ and the Tweet analysis. Importantly, the WSJ dataset only has 5 events during which Vague tensions decreased. In comparison, the Tweet dataset is sparse: it only has 1 event with decreased Vague tensions, 2 events with decreased Cars tensions, 2 events with ambiguous Steel tension, and several other low observation events. Furthermore, it is immediately obvious that in both datasets, the events with increasing tensions significantly outnumber the events with decreasing tensions; President Trump and his administration spend more time increasing trade pressure via threats and tariffs than on relieving that pressure through successful negotiations. This is especially evident in the Tweets dataset: President Trump increases trade tensions nearly three times as much as he decreases them.

Looking at the individual trade categories, the Chinese trade negotiations have by far the most events in both datasets. In both datasets, the Vague trade category is most unequally balanced; the WSJ Vague events are heavily ambiguous, whereas the Tweet Vague events increase tensions. In comparison, the NAFTA trade category seems relatively balanced in both datasets, as the NAFTA negotiations ended successfully in the United States-Mexico-Canada Agreement. It is interesting to note that although the WSJ dataset has almost an equal amount of increasing Cars tensions as it does ambiguous Cars tensions, President Trump never tweets ambiguously with regards to auto tariffs and, actually, heavily leans towards increasing tensions.

Table 2: WSJ Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	35	16	14	16	5	86
Ambiguous	34	19	21	27	31	132
Increased	58	21	22	34	10	145
Total	127	56	57	77	46	363

Table 3: Tweet Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	12	6	2	4	1	25
Ambiguous	12	4	0	2	6	24
Increased	14	10	8	11	29	72
Total	38	20	10	17	36	121

IV. Firm-level Data

The above sections describe the various trade categories and news event datasets. These trade negotiations will naturally have a larger impact on those firms that have a larger exposure to the specific trade categories. In the following section, I describe the data collected on the production and revenue geography of each firm. This will allow me to more accurately assess how President Trump and his administration have impacted specific types of auto manufacturers, for instance those with high U.S. production, or those with high European production.

A. Firm-level Supply Chain Data Collection

Ideally, we would like to know how much firm X produces in country A for the local market in addition to how much firm X produces in country A that will then be exported to countries B, C, and D. Such a detailed breakdown of each firm's supply chain would allow my analysis to accurately determine the exposure of firm X to trade negotiations. The holy grail would be to have this information on the product level; to know the amount of, for instance, steel

that BMW imports from China in order to produce cars in the U.S. However, to my knowledge, this information is not available. Below, I outline two sources of supply-chain information that I use: 1) National Highway Traffic Safety Administration (NHTSA) data on vehicle content and 2) Auto manufacturer's self-provided statistics.

The NHTSA releases vehicle content data on each model sold in the U.S.⁵ Each model is composed of many parts, each of which might be produced in a different country. Additionally, the model might be assembled in a different country. Each country's value-add, in terms of parts and labor, is then calculated for each model and reported by the brand. Unfortunately, the NHTSA does not delineate between U.S. and Canadian content. For instance, a Toyota Rav4 has 35% of its value derived from U.S. and Canada, while 60% of its value derived from Japan.

From now on, I will refer to these percentages as the vehicle content with respect to X country: the U.S. and Canada content for the Toyota Prius is 35%. Importantly, a firm is only required to list foreign content for countries that have a vehicle content above 15%. Using this information from 2017 and 2018 in conjunction with model-level sales information from goodcarbadcar⁶, I calculate two statistics: 1) the average vehicle content per country for each auto manufacturer (a single auto manufacturer might own several brands, each of which produces many models) and 2) the percentage of sales per manufacturer that are from models with a NAFTA vehicle content above 62.5 percent—the previous threshold to achieve NAFTA free trade status.

Separately, I use self-reported statistics, especially annual reports, to collect information regarding production and revenue by country for each firm. I collect percentages on car production, employees, and number of plants per country for each firm. On the production side, I

⁵ Source: <https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports>

⁶ Source: <http://www.goodcarbadcar.net/2018/01/december-2017-year-end-u-s-vehicle-sales-rankings-top-296-best-selling-vehicles-in-america-every-vehicle-ranked/>

use the car production percentages when available. If these are not available for a particular country, I use the employee percentage for that country and, lastly, manufacturing plants for that country. Similarly, I collect revenue by country or, if revenue is not available, the number of cars sold in each country.

Thus, I have three firm-level statistics to group by: 1) the vehicle content of U.S. models 2) production percentages by country and 3) revenue percentages by country. Of these statistics, the U.S. and Canada vehicle content percentages most directly relate to U.S. import tariffs because low U.S. and Canada content percentage indicate a high reliance on imports. That said, these percentages are less relevant to retaliations by other countries because they provide no information regarding an auto manufacturer's U.S. exports to another country. In this case, the U.S. production figures, compiled from annual reports, are a better proxy for a firm's reliance on U.S. production for global sales.

B. Firm-level Supply Chain Data Splits

Below, in tables 4 and 5, I have reported the firm-level supply chain figures that are relevant to my analysis. For each set of statistics, I have divided the firms into a high and low split by their supply chain values. It is important to note that the below production percentages per firm do not necessarily add up to 100% because a particular firm's NAFTA production percentage might be calculated from sales data, whereas its European production percentage might rely on employment data.

Table 4: Firm Provided Data

stock	<u>Production</u>				<u>Revenue</u>
	NAFTA	US	Europe	China	China
bmw	0.20	0.17	0.91		0.19
daimler	0.13	0.13	0.62	0.20	0.12
fcau	0.49		0.33		0.04
ford	0.57	0.45	0.25	0.15	0.18
gm					0.42
honda	0.34	0.23	0.03	0.28	
hyundai	0.08	0.08	0.07	0.24	
kia	0.18	0.11	0.11	0.27	0.14
mazda	0.27	0.16	0.17	0.20	0.20
mitsubishi	0.00	0.00	0.00	0.11	0.04
nissan	0.30	0.16	0.14	0.27	0.26
subaru	0.33	0.33	0.00	0.00	0.03
tata	0.00	0.00	0.34	0.10	0.18
tesla	1.00	1.00	0.00	0.00	0.00
toyota	0.23	0.15	0.06	0.16	
volvo	0.02	0.02	0.79	0.17	0.21
vw	0.05	0.00	0.73	0.16	0.42

Splits
low
high

Table 5: NHTSA Foreign Content Data

stock	Vehicle Content		Percent of Models above 62.5% Threshold
	US & Canada	Mexico	NAFTA
bmw	0.14	0.00	0.00
daimler	0.25	0.00	0.13
fcau	0.58	0.22	0.93
ford	0.56	0.18	0.79
gm	0.49	0.24	0.71
honda	0.66	0.02	0.90
hyundai	0.26	0.00	0.00
kia	0.23	0.00	0.18
mazda	0.00	0.00	0.00
mitsubishi	0.00	0.00	0.00
nissan	0.30	0.15	0.38
subaru	0.24	0.00	0.00
tata	0.07	0.00	0.00
tesla	0.50	0.01	0.04
toyota	0.43	0.00	0.33
volvo	0.01	0.00	0.00
vw	0.08	0.14	0.00

Splits

low

high

C. Firm-level Stock Data

To construct a panel dataset of stock prices, I use Thomson Reuter’s DataStream⁷ to calculate the daily stock returns of 17 auto manufactures: BMW, Daimler (Mercedes-Benz), Fiat Chrysler, Ford, General Motors, Honda, Hyundai, Kia, Mazda, Mitsubishi, Nissan, Subaru, Tata Motors (Jaguar Land Rover), Tesla, Toyota, Volvo, and Volkswagen. Thus, for each day I have 17 different stock returns and perform a panel regression analysis.⁸ These stock prices are from various foreign stock exchanges, so I use each firm’s relevant stock market index in order to

⁷ Collected via the DataStream portal at the UC Berkeley Library Data Lab.

⁸ In Appendix A, specifically in tables A.7 and A.8, I report the number of auto manufacturing firms located at each stock exchange and the total number of observations per exchange, accounting for exchange specific holidays.

construct a beta value for each firm. For instance, if a stock is located on the Frankfurt Stock Exchange, I will use the DAX 30 daily return to calculate that firm's beta value. These firm level beta values control for the various levels of cyclicity each firm exhibits and any market-wide shocks.

V. Regression Analysis

The above sections have provided backgrounds for each trade category, compared the WSJ dataset with the Tweet dataset, and described the firm level data necessary to split firms. In this section, I describe and report the results of my analysis.

A. Regression Equation

$$Y_{i,t} = \alpha^{(c)} + \delta_i^{(c)} + \beta_i^{(c)} * \text{Reg}_{i,t} + \sum_{k=-1}^{+1} \gamma_k^{(c)} \{t \in c\} \{\text{Tension}=k\} + \sum_{k=-1}^{+1} \xi_k^{(c)} \{t \in c\} \{\text{Tension}=k\} \{i \in \text{split}\} + \epsilon_{i,t}^{(c)}$$

In the above equation, c represents the trade category of interest, i represents an individual firm, and t represents a particular day. For every regression, I specify the trade category, c, and the split that I would like to analyze for that trade category. These splits are by the firm-level data presented in section IV; they are used to test the hypothesis that firms with high production in the U.S., for instance, respond differently to news events than firms with low production in the U.S.

Y represents the daily stock return, $\alpha^{(c)}$ represents a constant, $\delta_i^{(c)}$ is the fixed effect for firm i, $\beta_i^{(c)}$ is the beta term for firm i with respect to firm i's regularizing index, Reg, and $\epsilon_{i,t}^{(c)}$ is

the error term for firm i on date t along the trade category c . The firm-level beta values are calculated in the regression to control for the fact that some stocks follow their respective indices more closely than others; they control for the various levels of cyclicality each firm exhibits and any market-wide shocks. Additionally, I use clustered standard errors by date to account for correlation that occurs amongst residuals of the same day⁹.

To estimate the impact of trade tensions along a trade category, I first include an indicator variable to make sure that day t has an event pertaining to trade category c . Then I include dummy variables for each level that trade tensions can take on: -1 for decreasing tensions, 0 for ambiguous tensions, and +1 for increasing tensions. This impact is realized by coefficient $\gamma_k^{(c)}$, where k stands for the Tension level.

To measure the differential impact on firms in the higher split, I include dummy variables for each Tension level along the trade category c . However, this second set of dummy variables is multiplied by an indicator variable that equals 1 if firm i is in the higher split. This differential impact on the higher split is realized by coefficient $\xi_k^{(c)}$, where k stands for the tension level.

Thus, $\gamma_k^{(c)}$ will be statistically significant if stocks in the lower split respond significantly to a news event of level k in trade category c . In comparison, $\xi_k^{(c)}$ will only be statistically significant if firms in the higher split respond differently than firms in the lower split. It is important to note that a significant $\xi_k^{(c)}$ does not imply that high-split firms react significantly to news events, rather it only measures the differential impact of those events on the higher split firms with respect to lower split firms.

⁹ I cluster by date rather than by stock because it is unlikely that the residuals are correlated by firm: firms that are less exposed to trade negotiations will have under-predicted stock price returns following good news, but over-predicted stock price return following bad news. An analogy is to the example where one clusters by classroom to account for the fact that each student is being affected by the same teacher. In our case, the classroom is a news event and the students are the stocks (Angrist and Pischke).

B. Expectations

Below, I outline the expected results of my analysis to build an intuition with regards to the actual results.

WSJ vs Tweet Events

By separately collecting data on the WSJ and the Tweet dataset, I not only test the impacts of trade negotiations on auto manufacturers, but also if the events picked up by the WSJ impact stock prices differently than President Trump's Tweets. The WSJ dataset captures a broad set of trade events that cover even the minute events, whereas the Tweet dataset is perhaps closer to President Trump's personal thoughts and intentions. Thus, I expect the tweets concerning cars to have the largest impact on stocks, especially due to their threatening nature. That said, the large number of WSJ events will predispose the WSJ analysis to produce smaller standard errors and, thus, more statistically significant results. For instance, the WSJ has 57 events relating to the Cars trade category, whereas the Tweet dataset has only 10.

Trade Categories

If we assume that the trade negotiations are having their intended effects, namely that they are helping U.S. auto manufacturers, then we expect splits with high U.S. production to perform relatively better in response to increasing trade tensions. This corresponds to statistically significant $\xi_k^{(c)}$ coefficients. If the tariffs would increase production costs of foreign manufacturers substantially, then domestic manufacturers might benefit from those tariffs—they are able to undercut the prices of foreign manufacturers and gain market share. This would be expressed in a significantly positive $\xi_{+1}^{(c)}$. However, if tariff tensions decrease, then the likelihood of such an outcome should diminish—causing low U.S. production firms to outperform high U.S. production firms. This corresponds to a significantly negative $\xi_{-1}^{(c)}$. The $\xi_0^{(c)}$ coefficient is hard to

interpret because ambiguous news events might indicate that more negotiations are necessary before a resolution is found, which may or may not impact firms differently. Additionally, my ambiguous marking might be biased; it may be the case that more of the ambiguous events are actually events that caused tensions to increase rather than decrease. Ultimately, I expect $\xi_{+1}^{(c)}$ to be statistically significant and positive, whereas $\xi_{-1}^{(c)}$ to be statistically significant and negative when splitting on U.S. production.

Since the trade categories vary in their impact on firms, I also expect variation in the $\xi_k^{(c)}$ coefficients by trade category. The car tariffs threats and NAFTA negotiations should have the largest magnitude $\xi_k^{(c)}$ coefficients since they have the largest potential impact on car manufacturers. The Steel and Aluminum negotiations should have the third largest impact as many U.S. auto manufacturers rely on steel or on parts that are produced using imported steel. The China negotiations should have similarly sized impacts as the Steel and Aluminum negotiations since they impact those U.S. producers that use Chinese auto parts and those U.S. producers that either export cars to China or that have Joint Ventures with China. Lastly, the Vague category is hard to rank as its contents concern President Trump's general position on trade negotiations. They increase uncertainty and increase the likelihood of tariffs, but it is hard to gauge their relative importance vis-a-vis the four definitive categories.

C. Results

I split the results of the regression analysis into two sections. First, I compare the impacts of each trade category on firms with high U.S. production versus firms with low U.S. production. These regressions evaluate the effectiveness of the Trump Administration's trade policy. Second, I look at each trade category individually and assess if these trade category negotiations have had

impacts along other firm splits. These regressions attempt to assess the broader impacts of the trade negotiations on the auto manufacturing industry.

i. Comparing High U.S. Production Firms with Low U.S. Production Firms

In order to compare high U.S. production firms with low U.S. production firms, I split firms based on two separate characteristics. First, I split firms based on the U.S. and Canada vehicle content. Since the U.S. is grouped with Canada in the NHTSA data, I also split firms based on the firm's production in the U.S., as collected from their annual reports. While firms with less U.S. production are more likely to rely on importing cars into the U.S., firms with high U.S. production might also rely on imported cars to supplement local U.S. production. I only interpret the interaction term, i.e. the $\xi_k^{(c)}$'s, because I am evaluating if the trade negotiations have impacted a select group of firms differently; the Trump Administration does not want to simply impact all firms, but rather incentivize firms with low U.S. production to become firms with high U.S. production.

I first look at WSJ events using the split by U.S. and Canada content in table B.1. The high U.S. and Canadian content firms only react statistically differently to news along the China and NAFTA trade categories. However, these differences are only for the events with an ambiguous change in trade tensions, which, as I have described previously, are not easily interpretable. Surprisingly, the high U.S. and Canada firms do not react significantly different from the low U.S. and Canada content firms with regards to trade events that either increase or decrease trade tensions.

Moving on to table B.2, I report the same regressions using WSJ events, however this time I split by U.S. production. Again, the results are mostly inconclusive; high U.S. production

firms react insignificantly different from low U.S. production firms along every trade category except for NAFTA. The NAFTA trade category does, however, offer strong evidence. Firms with high U.S. production outperform firms with low U.S. production by 0.397% on days with increasing NAFTA tensions. High U.S. production firms outperform low U.S. production firms because low U.S. production firms will either be hurt more by stricter NAFTA requirements, due to reliance on either Canada or Mexico, or due to the increased likelihood of higher tariffs on auto imports.

Overall, the WSJ analysis seems inconclusive. While it seems that high U.S. production firms outperform low U.S. production firms in with respect to increasing NAFTA tensions, the other splits returned no interpretable significant differences, even along the U.S. and Canada split. Having performed the relatively inconclusive WSJ analysis, I move onto the Tweet Analysis.

Table B.3 reports the results for the Tweet events using the U.S. and Canada content split. At first glance, both the Steel trade category, for decreasing tensions, and the Vague trade category, for increasing trade tensions, return significant results. Yet there is only one Tweet that has decreasing trade tensions along the Vague category, making this statistical significance not robust; the coefficient seems to indicate that firms with high U.S. and Canada content respond more favorably towards decreasing tension along the Vague trade category, which runs counter to expectations. In comparison the Vague trade category has 11 tweets that increase tensions, making the coefficient more robust, and the negative coefficient follows expectations: U.S. tariffs on steel and aluminum hurts the U.S. plants that require imported steel to produce cars and car parts. Since firms with high U.S. and Canadian content are more likely to be assembling cars from start to finish in the U.S., rather than assembling them elsewhere and importing them into

the U.S., high U.S. and Canadian content firms are at a higher risk of depending on foreign steel and aluminum. Thus, high U.S. and Canadian content firms underperform low U.S. and Canadian content firms by 0.405% on days with increasing tensions along the Steel trade category; the Steel and Aluminum trade negotiations hurt U.S. based auto manufacturers.

When splitting on U.S. production in table B.4, the Tweet analysis is inconclusive. Again, the Steel and Aluminum trade category produces significant results. However, the coefficient is only significant at the 10% level and there are only 4 days with Tweets of decreasing tensions along the Steel and Aluminum trade category, making even this result questionable. That said, the coefficient's polarity does align with expectations: since high U.S. production firms rely more on U.S. imports of steel and aluminum, high U.S. production firms should react more positively to news of decreasing Steel and Aluminum tensions. In fact, high U.S. production firms outperform low U.S. production firms by 1.045% on days with decreasing Steel and Aluminum tensions.

Taken in sum, the Tweet analysis is inconclusive: while the Steel and Aluminum trade category produces significant results via both splits, none of the other trade categories seem to have a differential impact on U.S. auto manufacturers. This is surprising since one would have expected the NAFTA and Car-related tweets to have a larger impact on firms than the Steel-related tweets. Additionally, the Steel and Aluminum results suggests that the trade negotiations have disadvantaged U.S. auto manufacturers. In comparison, the WSJ analysis did show that high U.S. production firms benefit from increasing NAFTA tension. Yet again, the big trade category, Cars, did not significantly benefitted U.S. auto manufacturers. Are President Trump's threats of auto tariffs not important? Or are they important, but only to a smaller subset of non-

US manufacturers? My next analysis takes a deeper dive into each of the trade negotiations to see if they have had a significantly different impact via non-US splits.

ii. The Impacts of Each Individual Trade Category

China

The China trade category produced no statistically significant differences between low U.S. production firms and high U.S. production firms. Although high U.S. production firms are more likely than low U.S. production firms to export to China, this does not appear to produce significant differences in stock returns. To further investigate the China trade category, I split the firms based on their Chinese revenue. Firms with high Chinese revenue are more likely to be shipping cars to China. Although not all of these firms have high U.S. production, they might still use their U.S. production facilities in order to ship cars to China.

The results of these regressions are presented in table C.1 of the appendix. Indeed, using the WSJ dataset, firms with high Chinese revenue respond 0.252% worse to news of increased China trade tensions. The WSJ events might be returning a more statistically significant coefficient than the Tweets due to their breath of event coverage and the fact that the tweets are not overly hostile.

NAFTA

The NAFTA trade category is perhaps the most disruptive trade category, barring outright threats of auto tariffs. The previous analysis showed that increasing NAFTA trade tensions causes high U.S. production firms to outperform low U.S. production firms, but only with the WSJ dataset. Yet, the NAFTA trade negotiations will more directly harm those firms

that have production facilities in Mexico and Canada, as these facilities depend on trade with the U.S. and, thus, will have to comply with stricter NAFTA rules to keep their tariff exemptions.¹⁰

Unfortunately, the self-reported production data on Canada and Mexico is quite sparse. Thus, I split firms by their NHTSA Mexican vehicle content¹¹ and provide the resulting regression in table C.2 of the appendix. The results align with these expectations and are significant: firms with high Mexico content respond 0.891% worse than firms with low Mexico content to news of increased NAFTA trade tensions. Although the Tweet events produce coefficient of the right sign, they are not statistically significant. Again, it seems as if the breadth and number of WSJ events have a more significant impact than President Trump's tweets.

The NAFTA negotiations also result in a higher risk of general auto tariffs in order to incentivize firms to comply with the stricter NAFTA requirements. Since President Trump has consistently singled out European auto manufacturers in his auto tariff threats, I split firms based on their European production and report the results in table C.2 of the appendix. This time the WSJ analysis is insignificant, whereas the Tweet analysis produces results that are significant and large: firms with high European production respond 0.535% worse to Tweets of increasing NAFTA tensions than firms with low European production. Perhaps since President Trump has tweeted about placing tariffs on European auto manufacturers, the market quickly links tweets concerning NAFTA to other tweets concerning European auto manufacturers. The Tweets are building a story concerning President Trump's personal motives and initiatives. Overall, the NAFTA negotiations seem to incentivize firms to shift production away from Mexico and Europe to the U.S.

¹⁰ Recall that the interparty share of trade within the NAFTA region is significantly high: over 40% of the trade in transportation goods with Mexico is related-party imports or exports.

¹¹ Recall that the NHTSA does not delineate between U.S. and Canadian content

Cars

The Cars trade category contains overt threats of tariffs on imported autos and auto parts. Thus, out of all the trade categories, they should have the most harmful impacts on auto manufacturers and, more specifically, those manufacturers that import autos and auto parts. However, in the previous analysis using U.S. splits, the results were insignificant. This is likely to have occurred because the threats to auto tariffs have frequently occurred following negotiations with the EU; President Trump likes to point to the high European tariffs on U.S. cars in comparison to low U.S. tariffs on European cars. Thus, I split firms based on European production and present the results in table C.3 of the appendix.

Again, the WSJ events produce insignificant results, while the tweet events produce significant results: firms with high European production respond 0.863% better than firms with low European production to Tweets that decrease auto tensions. Yet, it is important to note that there are only 2 tweets with decreasing tension along the Cars category, making this result not necessarily robust. While the WSJ analysis produces similar results, they are not statistically significant, which suggests that the Tweets are more relevant to auto-related tariffs, perhaps because President Trump is overtly hostile to European auto manufacturers in his tweets, whereas his administration is more tempered.

Another important split is by the percent of models that each manufacturer produces with a NAFTA content above 62.5%. These models fulfill the current NAFTA free trade requirements and will be exempt from any tariffs on auto imports. I report the results of this split in columns 2 and 4 of table C.3 in the appendix. This time, the tweet dataset provides no significant results, whereas the WSJ analysis does: firms with a high percentage of NAFTA fulfilling models underperform firms with low fulfillment by 0.725% in response to news of decreasing auto tariff

tensions. Firms with less exposure to the auto tariffs are not as sensitive to news of decreasing tensions. The Tweet dataset provides no significant results along this NAFTA split perhaps because of the few auto-related tweets, or perhaps because the President Trump tweets have been heavily Eurocentric. Either way, the NAFTA and Cars trade categories do provide evidence of the importance of President Trump's tweets to the auto manufacturing industry.

Overall, these results suggest that the trade negotiations have incentivized firms to move production away from Europe and to NAFTA. In both sets of regressions, the significant result is along the decreasing tension category, perhaps indicating that the market expected increasing tensions and was surprised by news of decreasing tensions.

Steel and Aluminum

In the U.S. analysis, the Steel and Aluminum negotiations produced significant results along the U.S. splits, but only for the Tweet dataset and only for the U.S. & Canada content split; firms with high U.S. and Canadian content underperformed firms with low U.S. and Canadian content by 0.405% when tweets increased Steel and Aluminum tensions. Yet, the Steel and Aluminum trade negotiations were also heavily involved with the EU. And the EU's prompt retaliation to the Steel and Aluminum tariffs ultimately caused President Trump to threaten tariffs on autos and auto parts.

Since the Steel and Aluminum trade category and the Car trade category are so intertwined, the Steel and Aluminum trade category might have a disproportionate impact on European auto manufacturers. However, table C.4 of the appendix reports no evidence in support of this hypothesis: the high European production firms seem to only respond in a significantly different manner to WSJ events that have an ambiguous impact on tensions, which is not easily

interpretable and only significant at the 10% level. Thus, the jump from steel tariffs to auto tariffs is too large, perhaps because the Steel and Aluminum negotiations have encompassed many other trade partners and have also had major impacts on the agriculture industry via retaliatory measures.

Vague

The events in the Vague trade category pertain to all unspecific comments made by President Trump or his administration. Thus, it makes most sense to analyze their impact using the splits by U.S. production, which have already been produced above. That said, it might also be interesting to see the impact via a split on European production, as President Trump has focused on the EU throughout the Cars events. In turn, the market might link any Vague trade comments to the likelihood of tariffs on European auto manufacturers.

In table C.5 of the appendix, I report the results of splitting by European production. The split produces highly significant results for news that decrease tensions: firms with high European production outperform firms with low European production by 0.601% in response to WSJ events with decreasing vague tensions but underperform firms with low European production by 0.416% in response to Tweets that decrease vague tensions. However, there are only 5 such WSJ events and 1 such tweet, weakening the WSJ result and perhaps completely nullifying the Tweet result. More reliable is the significant result, albeit at the 10% level, that firms with high European production underperform firms with low European production by 0.341% in response to tweets with increasing vague tensions—there are 29 such tweets. Overall, the relationship between vague news events and European firms seems weak at best. Yet, the

significant results for the Tweet dataset support the notion that tweets are a useful policy tool for President Trump, a result that is also supported by the NAFTA and Cars trade categories.

VI. Conclusion

A. Results

While the NAFTA trade negotiations and the Steel and Aluminum negotiations had different impacts on firms with high rather than low U.S. production, there are more significant differences among other splits, especially the Mexico content split with NAFTA trade events, and the European production split with NAFTA and Cars events. This indicates that the Trump Administration has had marginal success at helping U.S. firms: some negotiations seem to directly help U.S. firms, while other negotiations seem to advantage U.S. firms by harming firms with production in other countries. Although significant results are not abundant, they mostly point to the fact that the trade negotiations have incentivized firms to shift more production to the U.S., which has been the Trump Administrations stated policy.

Additionally, there are no trade categories for which a particular split produces a significant result for both increasing and decreasing tension events. This suggests that the market views increasing and decreasing news differently: while increasing tensions along a trade category might have been expected and, thus, do not have a significant impact on stock prices, decreasing trade tensions might be systematically unexpected along the particular trade category and, thus, impact stock prices. The market has certain default expectations regarding trade negotiations meaning that only events debunking these expectations trigger significant price changes.

Moreover, each of the trade categories had a statistically significant impact along one of the tested splits, but none of the splits had the same statistically significant result for both the WSJ and Tweet datasets, underscoring the fact that President Trump's tweets affect stock markets differently than WSJ events. This could suggest that even if President Trump's tweets contained the same objective content as a Trump Administration announcement, that the market would respond differently to the tweet due to its proximity to the president. At the same time, this result could suggest that the market responds equally to both news events if they contain the same objective content, but it just so happens that President Trump only tweets about certain events, causing the Tweets to not be representative of the entire Trump Administration policy. Most likely, both of these hypotheses are working at the same time, but since the Tweet results do not consistently produce more or less statistical significance than the WSJ results, more research is needed before coming to a decisive conclusion. Nonetheless, the results indicate the effectiveness of Tweets and suggests that future presidents might look to Twitter as an effective method of communication, as well as a political tool in negotiations.

B. Further Research

My research has shown that the trade negotiations have had a significant impact on auto manufacturers and that this impact can be measured using datasets compiled from WSJ articles and President Trump's Tweets. A more rigorous analysis would use news events from a Bloomberg terminal to more accurately pinpoint the time of an event. Whereas Bloomberg terminals report news almost instantaneously to stock traders, the WSJ reports news with a longer lag and not directly to stock traders. Such a Bloomberg dataset would replace the WSJ dataset and allow for an intraday analysis of stock reactions. If a Bloomberg analysis is done, it

might be worthwhile to write a program that automatically categorizes news events to not only speed up the data collection process, but to also have a more objective categorization process.

Further research could also apply my research methodology to other industries, such as the U.S. agriculture industry, which have been central to the trade negotiations. An analysis covering multiple industries would provide more information regarding the breadth of trade negotiation impacts. Similarly, more research could be performed to analyze the tweets of other important individuals, such as top government officials and company executives. Such an analysis would determine if the significance of President Trump's tweets is unique to the presidency, or if the market responds in similar ways to tweets from other individuals.

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Appendix A: Data Creation

I. Step-by-Step Construction

Step 1) Collect news events

For each of the two news sources, WSJ and tweets, I create a separate dataset. While the tweets dataset is constructed from all of President Trump's 2017 and 2018 tweets, the WSJ dataset only covers those articles that contain the words "tariff" or "tariffs" and are published in 2018. The WSJ dataset is only for 2018 because I did not have enough time to read articles from 2017. Additionally, 2017 contains only a small portion of trade events because the only major trade negotiations going on concerned NAFTA, which picks up in speed throughout 2018.

Step 2) Discard irrelevant news events

I first read each of the articles or tweets and discard those that do not pertain to the trade negotiations. Of the 3,047 WSJ articles, only 520 articles are relevant. Of the 6,072 tweets, only 204 are relevant. Since some tweets are a link to a recently signed trade proclamation, or welcome a foreign representative, I exclude these tweets, leaving 187 remaining.

Step 3) Classify the news event's category

For each of these remaining articles or tweets, I first classify the category that the article or tweet falls under. Sometimes President Trump or his administration will make proclamations concerning trade deficits or tariffs without implicit or explicit reference to one of these categories, in which case the event is marked as falling under the Vague category. Additionally, there are some trade events that do not fall under the major four categories or this Vague

category. These are generally events concerning bilateral trade negotiations with Australia, TPP, or other smaller trade partners and are assembled in an ‘other’ category, which I discard.

Step 4) Classify the news event’s impact on trade tensions

I then proceed to assign each article a Tension score of either 1, -1, or 0 depending on if the article describes an event that has increased, decreased, or had an ambiguous impact on trade tensions. The point of creating a -1, 0, 1 scale for individual articles was to eliminate subjectivity that might result from a more continuous scale. For tweets, I replicate the same process. I also assign each article and tweet a News score of either 0, 1, or 2 depending on if the article’s event or the tweet would be expected to have a negligible impact, some impact, or large impact on stock prices. News ranks of 0 tend to be articles that are published after other articles have already described the event. News scores of 2 tend to be articles that concern themselves with the outcome of a recent round of trade negotiations.

On a practical level, the WSJ dataset has more relevant articles than the Tweet dataset has relevant tweets. Thus, the WSJ dataset might be more robust to being split by trade category. Below, in tables A.1 through A.6, I include summary statistics of both of these raw datasets. There are 519 WSJ articles, whereas there are only 187 tweets. For these articles and tweets, I first provide the frequency of each of the tension values, then I provide the frequency of each of the news ranks, and lastly provide the number of article or tweets that reference a particular channel. Since WSJ articles tend to reference multiple trade categories, the total amount of WSJ category references, 564, is greater than the number of WSJ articles, 519. While some tweets might reference multiple categories, they are in the vast minority, perhaps due to the character

limit on Tweets. Thus, the number of Tweet category references, 180, is less than the number of Tweets, 187.

Table A.1: WSJ Article Markings

Tension Marking	Freq.
-1	116
0	197
1	206
Total	519

Table A.2: WSJ Article Markings

News Ranking	Freq.
0	181
1	212
2	126
Total	519

Table A.3: WSJ Trade Categories

Category Referenced	Freq.
China	215
NAFTA	82
Steel and Aluminum	144
Cars	70
Vague	53
Total	564

Table A.4: Tweet Markings

Tension Marking	Freq.
-1	54
0	36
1	97
Total	187

Table A.5: Tweet Markings

News Ranking	Freq.
0	10
1	106
2	71
Total	187

Table A.6: Tweet Trade References

Category Referenced	Freq.
China	57
NAFTA	32
Steel and Aluminum	26
Cars	12
Vague	53
Total	180

Step 5) Collapse tension values by day

Multiple articles or tweets might occur on the same day and not have the same Tension value.

When this occurs, I only keep those articles or tweets that have the maximum daily News rank. I then average the Tension values for the remaining articles in order to get a Tension value for the given day. This daily Tension is a continuous variable between -1 and 1. For example, if day A has two articles with a Tension value of 1 and one article with a tension value of 0, then day A

has Tension value of $(1+1+0)/3= 0.67$. If day B has only one article that has a tension value of 1 then day B has a Tension value of 1. However, this makes the implicit assumption that day B has a larger impact on trade tensions than day A, despite the fact that day A has two articles with a tension value of 1. To eliminate these implicit assumptions, I create a polarized, discrete version of the Tension value that I call Pol. If a given day's Tension < 0 , then Pol = -1; if a given day's Tension = 0, then Pol = 0; if a given day's Tension > 0 , then Pol = +1. In this paper, I do not differentiate between Pol and Tension, but the final dataset and all of the regression analysis uses this discrete Pol variable.

Step 6) Analysis by Channel

For my analysis by trade category, I follow a similar process in order to assign each day a Pol value for each category by grouping articles not only by the day of publication but also by category. A given day might have more than one Pol value, each of which is connected to a specific trade category. Since events occurring on the weekend or on an exchange holiday will only impact the stock prices once the market opens on the next business day, I group all articles that are published on the weekend or on an exchange holiday to the next business day. On the next page, tables A.7 and A.8 report the number of business days that have news events for each stock exchange and the total number of firms located on that stock exchange.

Table A.7: WSJ Events by Exchange

Location of Stock Exchange	Business Days with News	Number of Firms	Total Observations
Europe	201	4	804
Japan	198	6	1188
South Korea	194	2	388
US	200	5	1000
Total	793	17	3380

Table A.8: Tweet Events by Exchange

Location of Stock Exchange	Business Days with News	Number of Firms	Total Observations
Europe	102	4	408
Japan	100	6	600
South Korea	100	2	200
US	100	5	500
Total	402	17	1708

A potential concern is that the average trade tensions per day could be close to 0, but be assigned a -1 or +1 in the discretized version of Tension. Below, in tables A.9 and A.10, I tabulate the average daily tensions in order to demonstrate that there are very few days with average tensions close to 0, but not 0.

Table A.9: WSJ Daily Tension

Average Tension	Freq.	Percent
-1	77	21.21
-0.67	2	0.55
-0.5	3	0.83
-0.33	3	0.83
-0.25	1	0.28
0	132	36.36
0.33	1	0.28
0.5	11	3.03
0.67	1	0.28
1	132	36.36
Total	363	100.00

Table A.10: Tweet Daily Tension

Average Tension	Freq.	Percent
-1	23	19.01
-0.6	1	0.83
-0.5	1	0.83
0	24	19.83
.5	2	1.65
1	70	57.85
Total	121	100.00

II. Comparison of Classification of WSJ and Tweet Dataset

In the datasets, without considering trading holidays and considering all trade categories at once, the WSJ identifies 205 days and the Tweet analysis identifies 102 days. Of these days, 74 occur in both datasets. Yet, these datasets disagree on the Pol value for 35 of these 74 events. Below, in table A.11, I have tabulated these disagreements. When performing a correlation analysis using the 74 days that overlap, the correlation between the WSJ Pol variable and the Tweet Pol variable is only 0.3948, showing that only 39.48% of the variance within the Tweet Pol variable can be explained by the WSJ Pol variable. Clearly, President Trump tweets offer a different account of the trade negotiations than the WSJ events, which are more representative of his administration's official stances.

Table A.11: Pol Variable Comparison

WSJ Pol - Tweet Pol	Freq.
-2 (WSJ = -1, Tweet = 1)	8
-1	12
0 (No disagreement)	39
1	12
2 (WSJ = 1, Tweet = -1)	3
Total	74

Appendix B: U.S. Split Results

Table B.1: WSJ Events Split by U.S. & Canada Content

	<u>Trade Category</u>				
	China	NAFTA	Cars	Steel	Vague
decreasing tension	0.0509 (0.117)	0.262* (0.150)	-0.205 (0.166)	-0.121 (0.145)	-0.179 (0.186)
ambiguous tension	-0.193* (0.109)	-0.196 (0.132)	0.174 (0.141)	0.149 (0.110)	-0.117 (0.116)
increasing tension	-0.168* (0.1000)	0.127 (0.145)	-0.222 (0.161)	-0.158 (0.111)	-0.315 (0.229)
high content X decreasing tension	0.00914 (0.189)	-0.129 (0.176)	-0.268 (0.264)	-0.240 (0.244)	0.0407 (0.326)
high content X ambiguous tension	-0.483*** (0.161)	0.263* (0.152)	-0.0676 (0.171)	0.174 (0.210)	0.195 (0.226)
high content X increasing tension	0.248 (0.162)	-0.213 (0.140)	0.151 (0.212)	0.0580 (0.216)	0.160 (0.248)
Constant	0.0400 (0.0695)	-0.0271 (0.0636)	0.00107 (0.0621)	-0.00162 (0.0653)	0.0144 (0.0652)
Observations	4,437	4,437	4,437	4,437	4,437
R-squared	0.279	0.274	0.275	0.276	0.273
Number of date	261	261	261	261	261
Number of Low Content Firms	11	11	11	11	11
Number of High Content Firms	6	6	6	6	6
Firm Fixed Effects	YES	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high U.S. & Canada Content and the dummied discrete tension variable. Each column represents the results of using the WSJ tension data pertaining to one of the five trade categories. The stock prices are from 2018 and the standard errors are clustered by date. Trade events are tabulated below.

WSJ Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	35	16	14	16	5	86
Ambiguous	34	19	21	27	31	132
Increased	58	21	22	34	10	145
Total	127	56	57	77	46	363

Table B.2: WSJ Events Split by U.S. Production

	<u>Trade Category</u>				
	China	NAFTA	Cars	Steel	Vague
decreasing tension	0.0933 (0.117)	0.229 (0.157)	-0.351* (0.200)	-0.234 (0.170)	-0.124 (0.245)
ambiguous tension	-0.341*** (0.0934)	-0.0416 (0.125)	0.148 (0.141)	0.128 (0.113)	-0.0637 (0.119)
increasing tension	-0.138 (0.0991)	-0.0278 (0.141)	-0.148 (0.163)	-0.179 (0.109)	-0.309 (0.204)
high production X decreasing tension	-0.163 (0.197)	-0.0206 (0.332)	0.219 (0.275)	0.114 (0.240)	-0.185 (0.325)
high production X ambiguous tension	-0.0923 (0.157)	-0.327 (0.311)	0.00619 (0.208)	0.354 (0.230)	0.0695 (0.232)
high production X increasing tension	0.248 (0.178)	0.397** (0.168)	-0.0917 (0.217)	0.177 (0.201)	0.209 (0.271)
Constant	0.0462 (0.0693)	-0.0239 (0.0627)	0.00482 (0.0620)	0.0102 (0.0653)	0.00702 (0.0648)
Observations	4,437	4,437	4,437	4,437	4,437
R-squared	0.277	0.274	0.275	0.276	0.273
Number of date	261	261	261	261	261
Number of Low Production Firms	11	11	11	11	11
Number of High Production Firms	4	4	4	4	4
Firm Fixed Effects	YES	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high U.S. Production and the dummied discrete tension variable. Each column represents the results of using the WSJ tension data pertaining to one of the five trade categories. The stock prices are from 2018 and the standard errors are clustered by date. Trade events are tabulated below.

WSJ Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	35	16	14	16	5	86
Ambiguous	34	19	21	27	31	132
Increased	58	21	22	34	10	145
Total	127	56	57	77	46	363

Table B.3: Tweet Events Split by U.S. & Canada Content

	<u>Trade Category</u>				
	China	NAFTA	Cars	Steel	Vague
decreasing tension	0.191 (0.181)	0.0533 (0.281)	1.014*** (0.273)	-0.376*** (0.136)	-0.0283 (0.0247)
ambiguous tension	-0.168 (0.208)	-0.472** (0.223)		0.0605 (0.0412)	0.413** (0.200)
increasing tension	0.0934 (0.164)	-0.195 (0.202)	-0.429** (0.208)	0.0253 (0.206)	-0.0360 (0.131)
high content X decreasing tension	-0.296 (0.189)	-0.170 (0.347)	0.334 (0.250)	-0.496 (0.792)	0.163*** (0.0383)
high content X ambiguous tension	-0.00339 (0.241)	-0.0164 (0.170)		0.427 (0.786)	0.421 (0.655)
high content X increasing tension	-0.181 (0.270)	0.0460 (0.218)	0.335 (0.355)	-0.405** (0.181)	0.129 (0.247)
Constant	-0.0299 (0.0391)	-0.0204 (0.0393)	-0.0245 (0.0389)	-0.0250 (0.0394)	-0.0298 (0.0394)
Observations	8,857	8,857	8,857	8,857	8,857
R-squared	0.240	0.241	0.242	0.241	0.242
Number of date	521	521	521	521	521
Number of Low Content Firms	11	12	11	11	11
Number of High Content Firms	6	5	6	6	6
Firm Fixed Effects	YES	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high U.S. & Canada Content and the dummied discrete tension variable. Each column represents the results of using the Tweet tension data pertaining to one of the five trade categories. The stock prices are from 2017-18 and the standard errors are clustered by date. Trade events are tabulated below.

Tweet Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	12	6	2	4	1	25
Ambiguous	12	4	0	2	6	24
Increased	14	10	8	11	29	72
Total	38	20	10	17	36	121

Table B.4: Tweet Events Split by U.S. Production

	<u>Trade Category</u>				
	China	NAFTA	Cars	Steel	Vague
decreasing tension	0.0758 (0.180)	-0.0921 (0.320)	1.040*** (0.249)	-0.796** (0.324)	0.0349 (0.0242)
ambiguous tension	-0.226 (0.206)	-0.497*** (0.189)		0.0447 (0.120)	0.484** (0.244)
increasing tension	-0.0584 (0.187)	-0.195 (0.165)	-0.397* (0.208)	-0.0936 (0.201)	-0.00601 (0.139)
high production X decreasing tension	0.0268 (0.167)	0.415 (0.723)	0.391 (0.259)	1.045* (0.591)	-0.0241 (0.0395)
high production X ambiguous tension	0.241 (0.274)	0.0900 (0.304)		0.709 (0.738)	0.326 (0.628)
high production X increasing tension	0.380 (0.258)	0.0585 (0.265)	0.368 (0.438)	-0.109 (0.169)	0.0643 (0.206)
Constant	-0.0220 (0.0392)	-0.0185 (0.0393)	-0.0251 (0.0389)	-0.0193 (0.0395)	-0.0324 (0.0394)
Observations	8,857	8,857	8,857	8,857	8,857
R-squared	0.241	0.241	0.242	0.242	0.241
Number of date	521	521	521	521	521
Number of Low Production Firms	11	11	11	11	11
Number of High Production Firms	4	4	4	4	4
Firm Fixed Effects	YES	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high U.S. Production and the dummied discrete tension variable. Each column represents the results of using the Tweet tension data pertaining to one of the five trade categories. The stock prices are from 2017-18 and the standard errors are clustered by date. Trade events are tabulated below.

Tweet Events by Trade Category

Tension	China	NAFTA	Cars	Steel	Vague	Total
Decreased	12	6	2	4	1	25
Ambiguous	12	4	0	2	6	24
Increased	14	10	8	11	29	72
Total	38	20	10	17	36	121

Appendix C: Regression Results for Non-US Splits

Table C.1: Chinese Trade Category with Chinese Splits

	<u>WSJ Events</u>	<u>Tweet Events</u>
	Chinese Revenue	Chinese Revenue
decreasing tension	0.0609 (0.130)	0.0947 (0.203)
ambiguous tension	-0.395*** (0.110)	-0.199 (0.168)
increasing tension	-0.00544 (0.111)	0.0291 (0.197)
High revenue X decreasing tension	-0.0226 (0.108)	-0.0439 (0.168)
High revenue X ambiguous tension	0.110 (0.126)	0.0997 (0.210)
High revenue X increasing tension	-0.252** (0.116)	0.00413 (0.173)
Constant	0.0281 (0.0709)	-0.0254 (0.0395)
Observations	4,437	8,857
R-squared	0.277	0.240
Number of date	261	521
Number of Low Revenue Firms	9	9
Number of High Revenue Firms	5	5
Firm Fixed Effects	YES	YES
Firm-Level Beta Values	YES	YES
Clustered Standard Errors	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high Chinese revenue and the dummied discrete tension variable. The tension variable is specifically for the China trade category. Each column represents the results of using either the WSJ or Tweet dataset for the Chinese revenue split. The stock prices are from 2018 for the WSJ analysis and from 2017-18 for the Tweet analysis. The standard errors are clustered by date. Trade events are tabulated below.

Chinese Trade Category Events		
Tension	WSJ	Tweet
Decreases	35	12
Ambiguous	34	12
Increases	58	14
Total	127	38

Table C.2: NAFTA Trade Category with Mexico Content and European Production Splits

	<u>WSJ Events</u>		<u>Tweet Events</u>	
	Mexican Content	European Production	Mexican Content	European Production
decreasing tension	0.262* (0.139)	0.187 (0.158)	-0.0683 (0.335)	0.0428 (0.345)
ambiguous tension	-0.155 (0.131)	-0.0972 (0.152)	-0.444** (0.178)	-0.446** (0.199)
increasing tension	0.325** (0.162)	0.120 (0.159)	-0.0469 (0.218)	-0.0513 (0.145)
High split X decreasing tension	-0.131 (0.239)	0.161 (0.252)	0.246 (0.409)	-0.160 (0.364)
High split X ambiguous tension	0.124 (0.181)	-0.0906 (0.173)	-0.115 (0.242)	-0.135 (0.245)
High split X increasing tension	-0.891*** (0.235)	-0.232 (0.232)	-0.452 (0.335)	-0.535*** (0.156)
Constant	-0.0456 (0.0640)	-0.0143 (0.0627)	-0.0221 (0.0393)	-0.0101 (0.0396)
Observations	4,437	4,437	8,857	8,857
R-squared	0.277	0.274	0.241	0.241
Number of date	261	261	521	521
Number of Low Production Firms	12	12	12	12
Number of High Production Firms	5	4	5	4
Firm Fixed Effects	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high Mexican Content (or high European production) and the dummied discrete tension variable. The tension variable is specifically for the NAFTA trade category. Each column represents the results of using either the WSJ or Tweet datasets for the Mexican Content and European Production splits. The stock prices are from 2018 for the WSJ analysis and from 2017-18 for the Tweet analysis. The standard errors are clustered by date. Trade events are tabulated below.

NAFTA Trade Category Events		
Tension	WSJ	Tweet
Decreases	16	6
Ambiguous	19	4
Increases	21	10
Total	56	20

Table C.3: Cars Trade Category with NAFTA Compliance and European Production Splits

	<u>WSJ Events</u>		<u>Tweet Events</u>	
	European Production	NAFTA Compliance	European Production	NAFTA compliance
decreasing tension	-0.347** (0.162)	-0.129 (0.126)	0.930*** (0.151)	1.134*** (0.217)
ambiguous tension	0.202 (0.156)	0.173 (0.141)		
increasing tension	-0.179 (0.167)	-0.254* (0.154)	-0.271 (0.267)	-0.357 (0.266)
High split X decreasing tension	0.202 (0.361)	-0.725** (0.351)	0.863*** (0.213)	-0.00788 (0.150)
High split X ambiguous tension	-0.216 (0.148)	-0.101 (0.197)		
High split X increasing tension	0.0427 (0.228)	0.362 (0.225)	-0.169 (0.235)	0.198 (0.223)
Constant	0.00597 (0.0634)	-0.000407 (0.0627)	-0.0274 (0.0388)	-0.0261 (0.0388)
Observations	4,437	4,437	8,857	8,857
R-squared	0.275	0.275	0.242	0.243
Number of date	261	261	521	521
Number of Low Production Firms	12	12	12	12
Number of High Production Firms	4	5	4	5
Firm Fixed Effects	YES	YES	YES	YES
Firm-Level Beta Values	YES	YES	YES	YES
Clustered Standard Errors	DATE	DATE	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high European Production (or a high percentage of NAFTA complying models) and the dummied discrete tension variable. The tension variable is specifically for the Cars trade category. Each column represents the results of using either the WSJ or Tweet datasets for the European production and NAFTA compliance splits. The stock prices are from 2018 for the WSJ analysis and from 2017-18 for the Tweet analysis. The standard errors are clustered by date. Trade events are tabulated below.

Car Trade Category Events		
Tension	WSJ	Tweet
Decreases	14	2
Ambiguous	21	0
Increases	22	8
Total	57	10

Table C.4: Steel Trade Category with European Production Splits

	<u>WSJ Events</u>	<u>Tweet Events</u>
	European Production	European Production
decreasing tension	-0.316** (0.146)	-0.595* (0.322)
ambiguous tension	0.280** (0.119)	0.258 (0.371)
increasing tension	-0.129 (0.114)	-0.147 (0.189)
High production X decreasing tension	0.432 (0.289)	0.188 (0.610)
High production X ambiguous tension	-0.306* (0.165)	-0.196 (0.345)
High production X increasing tension	-0.0375 (0.167)	0.116 (0.259)
Constant	0.00248 (0.0673)	-0.0236 (0.0392)
Observations	4,437	8,857
R-squared	0.276	0.241
Number of date	261	521
Number of Low Production Firms	12	12
Number of High Production Firms	4	4
Firm Fixed Effects	YES	YES
Firm-Level Beta Values	YES	YES
Clustered Standard Errors	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high European production and the dummied discrete tension variable. The tension variable is specifically for the Steel trade category. Each column represents the results of using either the WSJ or Tweet dataset for the European Production split. The stock prices are from 2018 for the WSJ analysis and from 2017-18 for the Tweet analysis. The standard errors are clustered by date. Trade events are tabulated below.

Steel Trade Category Events		
Tension	WSJ	Tweet
Decreases	16	4
Ambiguous	27	2
Increases	34	11
Total	77	17

Table C.5: Vague Trade Category with Europe Splits

	<u>WSJ Events</u>	<u>Tweet Events</u>
	European Production	European Production
decreasing tension	-0.322 (0.252)	0.127*** (0.0265)
ambiguous tension	-0.0513 (0.146)	0.531 (0.367)
increasing tension	-0.216 (0.152)	0.0894 (0.116)
High production X decreasing tension	0.601** (0.234)	-0.416*** (0.0372)
High production X ambiguous tension	0.0156 (0.170)	0.121 (0.266)
High production X increasing tension	-0.194 (0.391)	-0.341* (0.189)
Constant	-0.000209 (0.0637)	-0.0201 (0.0397)
Observations	4,437	8,857
R-squared	0.274	0.242
Number of date	261	521
Number of Low Production Firms	12	12
Number of High Production Firms	4	4
Firm Fixed Effects	YES	YES
Firm-Level Beta Values	YES	YES
Clustered Standard Errors	DATE	DATE

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the results of regressing the 17 auto manufacturer's stock prices on a constant, firm fixed effects, a regularizing index, a dummied discrete tension variable, and an interaction between firms with high European production and the dummied discrete tension variable. The tension variable is specifically for the Vague trade category. Each column represents the results of using either the WSJ or Tweet dataset for the European production split. The stock prices are from 2018 for the WSJ analysis and from 2017-2018 for the Tweet analysis. The standard errors are clustered by date. Trade events are tabulated below.

Vague Trade Category Events		
Tension	WSJ	Tweet
Decreases	5	4
Ambiguous	31	2
Increases	10	11
Total	46	17