7 Web Appendix

7.1 Data Preparation and Additional Summary Statistics

7.1.1 Baseline Dictionaries

To arrive at our customized dictionary, we start from five established dictionaries that contain lists of words that are associated with negative sentiments. Some dictionaries do not have simple negative word lists, but instead indicate valence scores, i.e., they specify *how negative or positive* a word is on a predefined scale. As we are interested in constructing a simply list of purely negative words, we make slight changes to the valence-based dictionaries. The below section briefly describes the five dictionaries serving as a baseline for constructing our context-specific negative word list.

Harvard-IV-4 dictionary: This long-established general English dictionary was publicly available through the following website: http://www.wjh.harvard.edu/~inquirer/[14]. We relied exclusively on Ngtv negativity word list.

Hu and Liu (2004): The world list built by Hu and Liu (2004) relies on an evaluation of movie reviews, and thus includes also more colloquial words. We obtained this list of negative words through the following webpage: https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#datasets.

Loughran and McDonald: The dictionary created by Loughran and McDonald (2011) was developed based on companies' 10-K financial reports and is, thus, specific to finance and economics topics. The political conflict between the US and China is

[14]Now available via the Wayback Machine: https://web.archive.org/web/20211128094656/http://www.wjh.harvard.edu/~inquirer/Ngtv.html

characterized by economic and trade disputes, which is why we consider this dictionary a valuable addition. While the authors provide a negative and a positive word list, we only rely on the negative one. The dictionary was later augmented, and we rely on the 2020 version of their Master Dictionary, available through the following website: https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

AFINN: This word list was developed by Nielsen (2011), who manually assigned words with a score of between -5 and +5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment. We filter for negative scores and thereby obtain the corresponding negative word list. The original dictionary also contained some combinations of words, which are excluded in this word list. It is available here:
https://github.com/fnielsen/afinn/tree/master/afinn/data.

VADER (Valence Aware Dictionary and sEntiment Reasoner): This dictionary is specifically designed to capture emotions on social media, as explained in Hutto and Gilbert (2014). It is a comprehensive list of words, each of which was rated by a human on a sentiment scale from "[-4] Extremely Negative" to "[4] Extremely Positive." We use the mean score and classify all words with a negative mean score as negative. In addition, we clean the word list of emoticons and other special characters. We obtained the data from https://github.com/cjhutto/vaderSentiment/blob/master/vaderSentiment/vader_lexicon.txt.

7.1.2 Most Frequent Words

Table A1: Most Frequent Words in Articles Mentioning China or Mexico, Excluding Stopwords

China				Mexico			
All words		Negative words		All words		Negative words	
Word	*N*	Word	*N*	Word	*N*	Word	*N*
china	231,511	war	17,836	mexico	166,550	misstated	11,511
chinese	159,305	against	14,502	new	83,632	against	9,552
said	87,217	pressure	6,317	mexican	59,734	incorrectly	5,757
trade	64,984	tariff	6,302	said	56,829	need	5,652
china's	52,007	debt	5,960	story	55,385	pay	5,456
trump	47,914	concerns	5,802	border	41,044	incorrect	5,450
year	36,373	tensions	5,414	news	33,765	war	4,694
beijing	34,517	demand	5,189	trump	33,260	violence	3,701
president	33,453	threat	4,973	usatoday	31,940	stop	3,321
tariffs	32,745	hit	4,798	state	29,154	illegal	3,205
new	32,107	issues	4,546	states	27,049	death	3,182
united	30,926	need	4,383	version	26,712	wrong	3,044
one	30,496	risk	4,153	one	25,393	force	2,986
also	30,149	hard	3,945	president	25,139	threat	2,789
companies	29,948	fell	3,840	year	24,730	lost	2,770
states	29,033	cut	3,717	united	22,701	cost	2,694
government	28,359	force	3,642	also	22,460	issue	2,671
american	28,310	protests	3,618	american	21,612	issues	2,664
billion	26,712	lower	3,495	earlier	21,484	hit	2,623
last	24,869	dispute	3,413	city	19,672	killed	2,611
market	24,559	low	3,385	people	18,962	died	2,571
two	23,119	issue	3,376	first	18,606	hard	2,493
hong	21,620	cost	3,351	trade	18,170	crime	2,456
economic	20,626	imposed	3,302	two	17,953	low	2,434
years	20,225	fight	3,089	life	17,799	crisis	2,422
xi	20,168	pay	3,047	last	16,885	illegally	2,211
company	19,833	impose	2,970	years	16,618	threatened	2,207
foreign	19,389	accused	2,921	canada	16,107	tariff	2,167
officials	19,101	problem	2,820	following	15,519	emergency	2,082
state	19,048	stop	2,764	money	15,207	dead	2,019

7.1.3 *Newspapers in our Sample*

Our sample consists of 109 newspapers listed below in alphabetical order:

Alaska Dispatch News, Albany Business Review Online, Albuquerque Business First Online, American Banker, Anchorage Daily News, Arizona Capitol Times, Atlanta Business Chronicle Online, Austin American-Statesman, Austin Business Journal, Baltimore Business Journal, Baltimore Daily Record, Bangor Daily News, Barron's, Birmingham Business Journal, Boston Business Journal, Broward Daily Business Review, Buffalo Business First Online, Buffalo News, Business Courier of Cincinnati Online, Charleston Gazette, Charlotte Business Journal, Chicago Business Journal, Columbus Business First Online, Crain's New York Business, Daily Breeze, Daily Camera, Daily Herald, Daily Journal of Commerce (Oregon), Dallas Business Journal, Dayton Business Journal, Denver Business Journal, Deseret News, Fulton County Daily Report, Houston Business Journal, Idaho Business Review, Investor's Business Daily, Jacksonville Business Journal, Kansas City Business Journal, L.A. Biz, La Crosse Tribune, Las Vegas Sun, Lehigh Valley Business, LNP, Long Island Business News, Los Angeles Daily News, Louisville Business First Online, Memphis Business Journal, Miami Daily Business Review, Milwaukee Business Journal, Minneapolis/St. Paul Business Journal, Nashville Business Journal, New York Business Journal, New York Daily News, New York Post, Orlando Business Journal, Pacific Business News Online, Palm Beach Daily Business Review, Palm Beach Daily News, Philadelphia Business Journal, Phoenix Business Journal, Pittsburgh Business Times Online, Pittsburgh Post-Gazette, Portland Business Journal, Portland Press Herald, Press Democrat, Puget Sound Business Journal, Roll Call, Sacramento Business Journal, San Antonio Business Journal, San Francisco Business Times Online, Silicon Valley/San Jose Business Journal, Smart Business Cleveland, Smart Business Pittsburgh, South Florida Business Journal, St. Louis Business Journal, St. Louis Post-Dispatch, Star-Tribune, Tampa Bay Business Journal, Tampa Bay Times, The Arizona Daily Star, The Atlanta Journal - Constitution, The Boston Globe, The Capital (Annapolis), The Capital Times & Wisconsin State Journal, The Christian Science Monitor, The Columbian, The Daily Record, The Gazette, The Journal Record, The Mecklenburg Times, The National Herald, The New York Times, The News-Gazette, The Palm Beach Post, The Pantagraph, The Philadelphia Daily News, The Philadelphia Inquirer, The Salt Lake Tribune, The Santa Fe New Mexican, The Spokesman-Review, The Wall Street Journal, The Washington Post, Times of Northwest Indiana, Topeka Capital-Journal, Triad Business Journal, Triangle Business Journal, USA Today, Washington Business Journal, Wichita Business Journal.

7.1.4 Description of Political Conflict Measurement

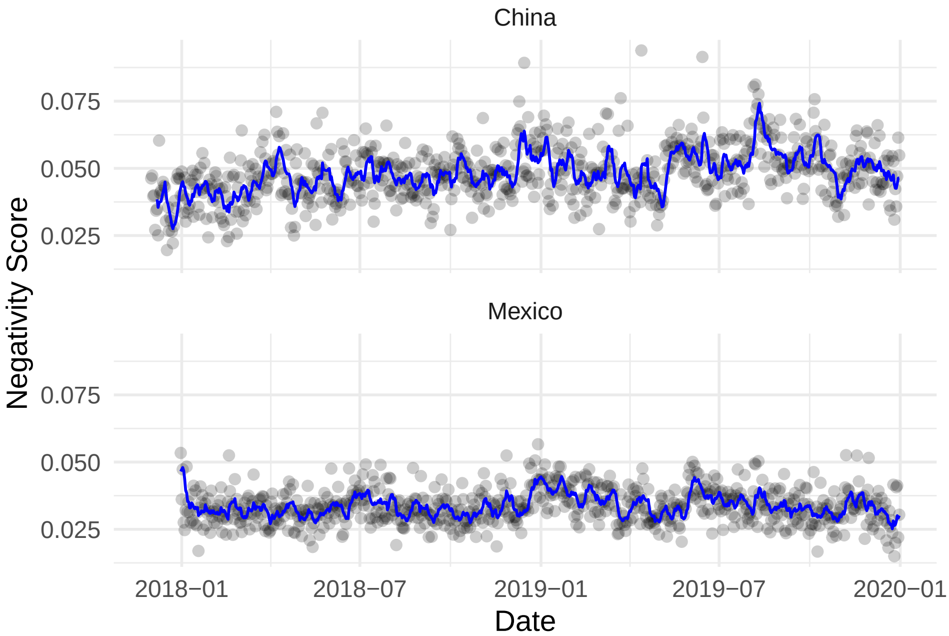
This section aims to provide the reader with a better understanding of how we measure political conflict and provide information on alternative measures, which we use in our robustness checks. The customized negativity dictionaries that we constructed for the purpose of this study are described in Section 3.2. These dictionaries are central to all of our measures of political conflict, whereby we consistently distinguish between China and Mexico-related conflict. For most of our measures, we consider the text corpus of articles and then calculate the share of negative words in all paragraphs mentioning the country of conflict (i.e., China or Mexico, respectively). The average of these scores then serves as a negativity score for the article.

After obtaining a negativity score at the article level, we aggregate the score up to the newspaper level, taking the average of the scores of all articles published by that newspaper on a given day. Finally, we take the average of all newspapers' negativity scores to arrive at a daily measure of negativity in reporting about China. The rationale here is that the reader will take away an overall impression from her daily read: the higher our score, the more negative is the reporting about China.

Our preferred measure of political conflict relies on newspapers' daily text-based negativity scores (*Text-based*). A newspaper's daily score is coded as missing whenever a newspaper does not mention China in any of its articles. Day-specific negativity scores are obtained through a simple average across all non-missing newspaper-specific scores. The final measure then averages across all day-specific negativity scores of the past seven days.

Figure A1 plots the day-level text-based measures for negativity in media reporting on China and Mexico, respectively. The blue lines indicate their seven-day moving averages, which correspond to our preferred measures of political conflict (*Negativity text*).

FIGURE A1: TEXT-BASED NEGATIVITY MEASURE FOR US-CHINA AND US-MEXICAN RELATIONS



Note: The dots indicate the daily negativity measure computed by averaging across newspaper-specific negativity. The blue line indicates its seven-day moving average.

Alternative Measures of Political Conflict (National Level)

To ensure the robustness of our preferred measure, we also compute three alternative series of political conflict. Firstly, we base our scores on the negativity of articles' headings mentioning China (*Heading-based*) instead of the negativity of the articles' texts. The intuition underlying this alternative approach is that headings are likely the most-read parts of an article. Nevertheless, the advantage of our text-based negativity series compared to the heading-based one is that we are able to capture the context of the China-related reporting better as we only analyze the negativity in the paragraphs containing the terms "China" or "Chinese" instead of the full article.

Secondly, we restrict the sample to the four largest newspapers in our sample (The New York Times, The Washington Post, USA Today, and The Wall Street Journal) and use their average negativity as a basis for our national series (*Four most-read newspapers*). While this approach ensures better comparability of sources concerning the size of newspapers' readership, it disregards the large heterogeneity in reporting styles across geographies. The four selected newspapers are also likely to mainly serve a particular type of reader.

As a final alternative, we weigh the negativity scores of newspapers by the size of their readership when computing the national negativity series, using circulation data from the Alliance for Audited Media (*Circulation-weighted*). While we would prefer this approach in principle, circulation data is only available for 25 out of 109 newspapers in our sample. Hence, we need to discard most of the available information to weigh newspaper's negativity by circulation. For this reason, we only use this metric for a robustness check instead of using it as the basis for our main analysis.

Table A2 presents the means and standard deviations of our four alternative measures of political conflict for China and Mexico, respectively. For completeness, the table also includes the summary statistics for our measure of reporting quantity. As explained in Section 3.2, we compute this measure to be able to control for the salience of the political conflict in the media irrespective of how negative its tone is. Table A3 proceeds by plotting the correlation among these five measures by country.

Alternative Measures of Political Conflict (State Level)

Table A2: Full Descriptive Statistics of Political Conflict Measures by Country

Country	Negativity metric	Mean	*SD*
China	Text-based (preferred)	0.0487	0.0062
	Heading-based	0.086	0.0132
	Four most-read newspapers 4	0.0532	0.0065
	Circulation-weighted	0.0525	0.0074
	Reporting quantity	317.0018	105.1826
Mexico	Text-based (preferred)	0.0336	0.0038
	Heading-based	0.0637	0.0067
	Four most-read newspapers	0.0422	0.0049
	Circulation-weighted	0.0403	0.005
	Reporting quantity	285.271	84.4586

Table A3: Correlation Among Alternative Political Conflict Measures

Country	Negativity metric	Reporting quantity	Heading -based	Text-based (preferred)	Four most-read newspapers	Circulation -weighted
China	Reporting quantity	1	0.44	0.57	0.56	0.55
	Heading-based	0.44	1	0.62	0.53	0.54
	Text-based (preferred)	0.57	0.62	1	0.81	0.85
	Four most-read newspapers 4	0.56	0.53	0.81	1	0.97
	Circulation-weighted	0.55	0.54	0.85	0.97	1
Mexico	Reporting quantity	1	0.3	0.46	0.47	0.43
	Heading-based	0.3	1	0.67	0.43	0.45
	Text-based (preferred)	0.46	0.67	1	0.68	0.73
	Four most-read newspapers	0.47	0.43	0.68	1	0.95
	Circulation-weighted	0.43	0.45	0.73	0.95	1

Besides relying on a US-wide measure of political conflict, we also exploit the differential reporting styles of newspapers across states (*State-level*). We use the location of a publisher's headquarters to assign newspapers to a state and construct state-level negativity scores as the average of all newspapers' scores from a given state. During this process, however, we make sure to exclude newspapers with a national and international as opposed to a more local audience when constructing these state-level series. We restrict the sample to states where our data covers at least two such local newspapers to accurately represent reporting styles at this regional level.

Similar to our preferred text-based negativity metric, our state-level measures also rely on the share of negative words in newspaper articles mentioning China. We average article scores up to daily newspaper scores and then obtain the daily state-level score as an average across all newspaper scores. For some states, there are days on which we do not record any articles mentioning China. On these days—where we lack “new signals"—we carry over the last recorded score from the last day there was any reporting about China. This approach follows the rationale that in the absence of new signals, the state of the conflict is perceived as unchanged. Finally, following our main measure of political conflict, we use the seven-day moving average of these daily scores as our final state-level negativity series.

The newspaper coverage of our data set varies slightly across states, which, by construction, induces differences in the series' levels and variation. This difference across states would render a quantitative interpretation of the coefficients difficult. Hence, we standardize each state-level series to have a mean of zero and a variance of one.

7.1.5 *Additional Summary Statistics on Daily Restaurant Visits*

Table A4 presents summary statistics on daily dine-in restaurant visits and the number of restaurants by restaurant type.

Table A4: Full Descriptive Statistics of Restaurant Visits by Restaurant Type

Restaurant sample	Mean visits	SD visits	Observations	Number of restaurants
All	74.28	85.77	140,978,726	193,926
Chinese	57.45	63.61	12,034,448	16,516
Mexican	72.58	79.30	21,754,281	29,887

7.1.6 *Correlation Between Dependent and Independent Variables*

Table A5 shows the correlation between our key dependent and independent variables for the Chinese and Mexican studies, respectively.

TABLE A5: CORRELATION BETWEEN RESTAURANT VISITS AND POLITICAL CONFLICT MEASURES BY COUNTRY

Country	Metric	Restaurant visits	Negativity text	Reporting quantity
China	Restaurant visits	1.00	0.05	0.03
China	Negativity text	0.05	1.00	0.57
China	Reporting quantity	0.03	0.57	1.00
Mexico	Restaurant visits	1.00	0.02	0.00
Mexico	Negativity text	0.02	1.00	0.46
Mexico	Reporting quantity	0.00	0.46	1.00

7.2 *Robustness Checks and Extensions*

7.2.1 *Time Series Estimation*

Besides our main specification, we also estimate how media reporting about China influences Chinese restaurant visits using a time series regression. Precisely, we estimate the following time series model:

$$\mathbb{E}[Visits_{it}|Negativity_t, \boldsymbol{X}_t', \gamma_i, t] = exp(\beta Negativity_t + \boldsymbol{X}_t'\boldsymbol{\mu} + \gamma_i + \delta \times t)\,, \qquad (2)$$

where β is the coefficient of interest stating how political conflict with China affects visits to Chinese restaurants. γ_i is a restaurant-fixed effect and t is a linear time trend. $\boldsymbol{X}_t$ represents further controls—depending on the specification—a holiday dummy, reporting quantity, and higher-order time trends.

This specification does not rely on the control group of non-Chinese restaurants, and is thus not at risk of violating the SUTVA assumption as our main specification in Equation (1). However, given the absence of a control group, we cannot control for the effect that general day-specific media reporting has on overall restaurant visits. If much of the temporal variation in restaurant visits is caused by factors that affect all restaurants in the same way, including general news, the above model would be estimated with considerable noise.

Table A6 shows the results of estimating Equation (2) and versions with higher-order time trends by OLS on the subsample of Chinese restaurants. Table A7 presents results from the equivalent model estimation using the entirety of restaurants in our sample.

Table A6: Time Series Poisson Regressions Using the Subsample of Chinese Restaurants

Dependent Variable:	Restaurant visits			
Model:	(1)	(2)	(3)	(4)
Variables				
Negativity	-3.270***	-3.267***	-3.629***	-4.006***
	(0.1331)	(0.1340)	(0.1531)	(0.1347)
Controls				
Reporting quantity	✓	✓	✓	✓
Holiday dummy	✓	✓	✓	✓
Time (linear)	✓	✓	✓	✓
Time (square)			✓	✓
Time (cubic)				✓
Fixed-effects				
Restaurant	✓			
Restaurant × Day of week		✓	✓	✓
Fit statistics				
Observations	11,952,103	11,952,081	11,952,081	11,952,081
Squared Correlation	0.57885	0.64772	0.64817	0.64882
Pseudo R^2	0.55551	0.60985	0.60999	0.61038

Notes: Clustered standard errors at the county level displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7.2.2 *Lagged Impact of Political Conflict on Consumption*

Through the analysis reported in Table A8, we test whether our measure of conflict is predictive of consumer behavior even several weeks after the release of the underlying media reports. Specifically, we include lags of our preferred independent variable that cover reporting in the previous weeks. As each of our daily variables captures the reporting negativity over the past week, adding the lags 7, 14, and 21 (days) avoids including regressors that are correlated by construction.

Table A7: Time Series Poisson Regressions using All Restaurants in the Sample

Dependent Variable:	Restaurant visits			
Model:	(1)	(2)	(3)	(4)
Variables				
Negativity	-2.070***	-2.004***	-2.148***	-2.597***
	(0.1584)	(0.1602)	(0.1678)	(0.1587)
Controls				
Reporting quantity	✓	✓	✓	✓
Holiday dummy	✓	✓	✓	✓
Time (linear)	✓	✓	✓	✓
Time (square)			✓	✓
Time (cubic)				✓
Fixed-effects				
Restaurant	✓			
Restaurant × Day of week		✓	✓	✓
Fit statistics				
Observations	140,014,391	140,013,653	140,013,653	140,013,653
Squared Correlation	0.59610	0.69025	0.69030	0.69128
Pseudo R^2	0.59756	0.66842	0.66844	0.66895

Notes: Clustered standard errors at the county level displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7.2.3 *Measures of Economic and Sociopolitical Dynamics*

For our robustness check in Section 4.3, we rely on three time series to proxy the evolution of economic sentiment and sociopolitical dynamics over time. We describe their construction in detail below.

Fed economic sentiment

We rely on the *Daily News Sentiment Index*, described in Buckman et al. (2020) and published by the San Fransisco Federal Reserve, to measure US economic sentiment over time.[15] Daily scores range from (-1) for the most negative to (+1) for the most positive sentiment and rely on a lexical analysis of economics-related newspaper

[15]The daily series can be downloaded here:

https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/.

Table A8: Main Poisson Regression with Lags Our Main Measure of Political Conflict

Dependent Variable:	Restaurant visits			
Model:	(1)	(2)	(3)	(4)
Variables				
Chinese × Negativity (t)	-1.266***	-1.165***	-1.183***	-1.199***
	(0.1640)	(0.1392)	(0.1364)	(0.1370)
Chinese × Negativity ($t-7$)		-0.2770***	-0.3601***	-0.3691***
		(0.0963)	(0.0781)	(0.0781)
Chinese × Negativity ($t-14$)			0.2164**	0.1096
			(0.1030)	(0.0905)
Chinese × Negativity ($t-21$)				0.2930***
				(0.0823)
Controls				
Chinese × Time	✓	✓	✓	✓
Chinese × Reporting quantity	✓	✓	✓	✓
Fixed-effects				
Date	✓	✓	✓	✓
Restaurant × Day of week	✓	✓	✓	✓
Fit statistics				
Observations	112,011,237	112,011,237	112,011,237	112,011,237
Squared Correlation	0.70498	0.70498	0.70498	0.70498
Pseudo R^2	0.67918	0.67918	0.67918	0.67918

Notes: Clustered standard errors at the county level displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

articles from US-based newspapers. We compute the 7-day moving average of this series to ensure temporal comparability to our measure of political conflict.

The correlation between our series of political conflicts and the *Fed economic sentiment* index is -0.581. The high correlation makes sense both due to the underlying economic relationship and the construction of both series. On the one hand, the US-Chinese political conflict is economically driven, and China is strongly related to the US economy. The fact that the newspapers underlying both series are both sourced from Factiva and both are based on a lexical approach to measuring sentiment further explains the high correlation.

RPNA economic sentiment

As an alternative to this series, we also create a sentiment series based on the full edition of the *RavenPack News Analytics (RPNA)* data (version 4). RPNA determines events' sentiment scores by systematically matching stories typically categorized by financial experts as having a short-term positive or negative stock price impact. We download the event sentiment scores (ESS) for all events published in newspapers worldwide that are marked with the place tag of the US. We obtain day-specific ESS scores by averaging across all daily events, standardizing the values, and computing our final sentiment index as the 7-day moving average of these scores. The final index reflects the economic news sentiment about the US more generally, with higher scores indicating more positive sentiment. The correlation between our series of political conflict between the US and China and the *RPNA economic sentiment* index is -0.276.

Number of tweets by President Trump

We consider President Trump's Twitter activity a prominent impulse for sociopolitical dynamics. Therefore, we use the average number of tweets over the past seven days as a control variable to account for variations in the political landscape. President Trump's tweets often announced new policies and set the tone for the political debate, including the political conflict with China. Additionally, those tweets repeatedly conveyed negative sentiment about foreign countries, and China in particular.