Global Trade, National News Frames, and State Public Opinion:

Making Sense of U.S.-China Trade, 2008-2018

by

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A dissertation submitted in partial fulfillment of
the requirements for the degree of

Doctor of Philosophy

(Mass Communication)

at the

University of Wisconsin—Madison

2020

Date of final oral examination: 8/11/2020

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Acknowledgement

The successful completion of an interdisciplinary dissertation rests on the support of many academics, friends, and family. First, I am deeply grateful to my committee. To my Ph.D advisor, Dr. Doug McLeod, thank you for encouraging my interdisciplinary endeavors. I owe my professional savvy to Dr. Dhavan Shah, who was a wealth of pragmatic knowledge about being an academic. No scholar has fueled my intellectual curiosity as Dr. Lewis Friedland, who was always ready with a new book and good conversation. Dr. Jon Pevehouse was incredibly welcoming, and we spent many hours talking about time series and international relations. And Dr. Anja Wanner emboldened me to incorporate corpus linguistic methods to my research.

It truly takes a village to raise a Ph. D student, and I am in debt to the many departments that supported me. The School of Journalism and Mass Communication is the best academic "home" I could have found. Many academic and professional professors on the 5th floor of Vilas played pivotal roles in my graduate school education. I am also grateful to the Political Science and English Language and Linguistics departments for taking me on as a Ph.D minor student. I have loved being in your classes, seminars, colloquiums, and research groups.

Third, my academic career would not have been possible without a phenomenal graduate student community. I am fortunate to have done research with many UW-Madison students, including: Aman Abhishek, Carlos Davalos, Larissa Doroshenko, Omar DumDum, Jordan Foley, Jianing Li, Gryffin Loya, Sang Jung Kim, Ayellet Pelled, Prathusha Sarma, Jordan Sallis, Min-Hsin Su, Jiyoun Suk, Zhongkai Sun, Chau Tong, Yiping Xia, CV Vitolo-Haddad, and Yini Zhang. Thank you for making me a more rigorous, thoughtful, and passionate scholar.

Fourth, I would like to express my sincerest gratitude to my friends and family for their support. My mother, Khian Lukito, and brother, Brian Lukito, have always encouraged me to pursue my academic dreams. A million thanks as well to Laura Chang, Vernon Rogers, and Linden Kawamura. I miss you all so much, and I can't wait to see you!

Finally, to John, who has now officially survived my Ph.D: you are the co-author of my life, and I would not have been able to complete this dissertation without you. Thank you.

Abstract

Though scholars have often recognized the importance of news media in explaining foreign trade policy and globalization, few studies have empirically tested the relationship between the economic impacts of trade, news media, and public opinion. One key factor potentially mediating their relationship is geography: how increasing international trade influences a country may vary depending on local economies. At the same time, local news organizations (and audiences) have shifted their focus toward national news, which may also mean that people are not consuming local information about trade consequences.

Using the U.S.-China trade shock as a case, I explore how national and state-level news media framing of U.S.-China trade and the manufacturing job market relate to U.S. citizens' perceptions of the local job market and U.S. President. The China shock refers to the economic impact of increasing Chinese export on the domestic economy, with a specific focus on how exports harmed domestic manufacturing employment. To analyze the relationship between the China shock, news coverage of U.S.-China trade, and public opinion, I begin with a linguistically informed framing analysis of news articles about U.S.-China trade in national print media, national television, and state-level newspapers. The three news frames—pro-trade, anti-trade, and anti-China frames—are identified using lexico-syntactic, medium-specific, manually validated dictionaries. I then perform time series analysis to illustrate how the relationship between the China shock, news coverage, and public opinion vary by geographic region.

Results from my analysis highlight two opposing trends. First: the persistence of the China shock from 2008 to 2018 vary greatly, even in states that rely on manufacturing. However, news coverage about U.S.-China trade in in both local and national outlets focused on national economic trends. As a result, people's perception of both the local economy and national politics were informed by a misapplication of national information to the state-level context.

Keywords: China shock, trade news, news framing, state political economies, time series

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Chapter 1: Introduction

In the 21st century, globalization—the increasing interdependence of people, firms, and nations in the international economic system[1]—has profoundly impacted the U.S. economy. Though U.S. politicians have conventionally supported trade liberalization (more trade between countries with fewer restrictions), growing competition in domestic markets against cheaper imports, particularly from China, has harmed manufacturing employment; this effect is known as the China shock (Autor , Dorn & Hanson, 2013). Consequentially, trade with China is an increasingly salient issue in American politics (Noland, 2020), as exemplified by the United States' ongoing trade war with China.

The process by which people's political attitudes are shaped by U.S.-China trade is still relatively unclear. Trade preference scholarship points to two possible explanations (Nguyen, 2019): that people's perceptions of trade are motivated by self-interest (egotropic trade preference) or by national economic trends (sociotropic trade preference). Experiments have shown that information from stimuli can influence these attitudes (Schaffer & Spilker, 2019), but only a handful of studies have examined news as a critical source of that information.

In this dissertation, I make the case that national news media framing of U.S.-China trade, in addition to state-level economic factors, shaped people's opinions about their local labor market and the U.S. President over time. This is a glocalized (global-local) phenomenon involving global trade with China, national news coverage, and state-level consequences of trade shocks. Though the relationship between news media, economic trends and public opinion about the economy and the President varies geographically, I highlight the particularly important role

[1] Traditionally, globalization is understood to be an economic phenomenon with political, cultural, and societal implications (Fairclough, 2009; Simmons & Elkins, 2004).

of national news media and discuss the issues with applying national economic data to understanding the local economy.

Purpose of Study

This dissertation addresses several interdisciplinary questions in the fields of political economy and political communication. I contribute to the scholarship in three novel ways. First, I demonstrate the temporal relationship between news media framing of U.S.-China trade and people’s public opinion about the economy and the President, even when a China shock is not locally evident. This suggests that local and national news stories about U.S.-China trade can influence sociotropic public opinion and even result in a misapplication of national economic information to the local economic context.

Second, I show that the relationships between news media, economic trends, and public opinion varies geographically and temporally. Though egotropic and sociotropic trade preference literature has focused on the individual- and the national-level respectively, state-level economic and news media variation changes the way the public makes sense of the China shock’s consequences. The analyses presented in this dissertation highlight the importance of accounting for geographic variation when considering public opinion about the economy.

Finally, I make the argument for a greater consideration of linguistics in framing theory. This is especially important given the growing popularity of natural language processing as a method in political communication: computational methods can be tools for scholars to study nuanced language structures, but we should not haphazardly apply computational tools to our corpora for the sake of finding frames. With this in mind, I outline a strategy for analyzing framed communication through the perspective of computational and corpus linguistics.

Research Questions

In this dissertation, I ask three research questions. The first focuses on the framing of U.S.-China trade. The second focuses on how the China shock and news coverage about U.S.-China trade may shape public opinion. The third focuses on geographic variation.

1. How do news media frame U.S.-China trade relations?
2. To what degree do news coverage and manufacturing job loss (as a consequence of Chinese import penetration) influence public opinion about the local job market and the President?
3. To what extent do economic trends and news media's relationship with public opinion vary by geographic region (i.e., state)?

Research Design

To study the relationship between the China shock, news media coverage, and public opinion, I conduct several time series analyses from 2008 to 2018 at the state and national-level of analysis. Time series analysis is a family of longitudinal statistical models for studying the temporal dynamics within and between variables (Wells et al., 2020). The time series models presented in this dissertation consist of three groups of variables: economic variables (i.e., import penetration from China and manufacturing job loss), news variables (national broadcast and print coverage, and state-level print coverage), and public opinion about the economy (the local job market) and the President (presidential job approval and perceptions of how the President is handling the economy).

For news media coverage, I also study how both print and broadcast news outlets framed U.S.-China trade. To do so, I perform a frame analysis, focusing specifically on cue, statement, and argument frames that helped make sense of Chinese import penetration and its impact on the

U.S. economy (both in terms of jobs and goods). The goal of this frame analysis is to construct lexico-syntactic, manually-validated dictionaries that will identify news stories in the corpora that use language features indicative of a frame about U.S.-China trade. I will also make the case for why broadcast and print news require specialized frame dictionaries.

Definition of Terms

Public Opinion: Public opinion is defined as the collective opinion of U.S. citizens and residents about social, political, and economic things. Current public opinion scholarship relies on representative polls and surveys (Donsbach & Traugott, 2007), suggesting that public opinion is an aggregate of individual-level opinions. This study will focus on two aspects of public opinion (one local and one national): perceptions of the local job market and perceptions of Presidential job performance, especially as it relates to the economy.

Egotropic and Sociotropic Public Opinion: When thinking about how citizens' understanding of the economy shapes their political attitudes and behaviors, scholars find evidence for two explanations (Nguyen, 2019). First, the *egotropic explanation* posits that people are influenced by their personal economic circumstances. Alternatively, the *sociotropic explanation* argues that people are influenced by national economic conditions.

News Media. In this study, "news media" and "the press" will be used as synonymous terms. They constitute news organizations and the actors within them (including reporters, journalists, editors, producers, and others). The normative expectation of U.S. news media is to provide objective information (Schudson, 2001); however, news media must also contextualize and explain how news stories affect people's lives, which can involve some normative assessment.[2]

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[2] This is especially true in the modern hybrid media ecosystem, as journalists have shifted from a gatewatching capacity into a gatekeeping capacity (Bruns, 2005). In other words, news organizations have less control over what passes "through" a gate to the public, but still play an important role by evaluating and contextualizating the information available in the public sphere.

In this dissertation, I study two genres of news media: *print news media* content, which is written, and *broadcast news media* content, which is spoken and transcribed.

News Framing. News framing is a phenomenon in which journalists and other actors arrange information in a news story to elicit a response, intentionally or unintentionally. The framing process includes two steps (de Vreese, 2005): frame building, the factors that influence content production, and frame effects, the consequence of this communication. To study framing, communication scholars isolate and analyze "frames," the product of the frame building process. In this dissertation, I focus specifically on news frames in language, or linguistic news frames.

Free/Open Trade v. Protectionism. Countries can enact policies that either encourage trade (e.g., trade deals) or make trade harder (e.g., taxes on imports) between two countries. If there are fewer regulations or restrictions, trade between two countries is considered freer, more open, and more liberalized. Protectionism refers to policies that add limits on trade. This includes (but is not limited to) tariffs, taxes on imported goods; quotas, which limit the quantity of certain imported goods; and subsidies to domestic industries that compete with exports. In the United States, politicians have generally supported free trade policies until the last two decades (Irwin, 2020). Current President Donald Trump is a proponent of protectionist policies.

Tariffs. Tariffs are taxes imposed by one country on the imported goods from another country. Taxes are paid by the domestic consumers of the country imposing the tax. If Russia imposes a tariff on U.S. goods, this means that Russian consumers would pay an additional tax when purchasing goods imported from the United States. In the time frame being discussed, tariffs were the most discussed protectionist policy (President Bush, Obama, and Trump all employed tariffs during their time in office).

The China Shock. The term “China shock,” popularized in a study by Autor et al. (2016), posits that the growing trade deficit between the United States and China (i.e., that the United States was importing far more than it was exporting from China) resulted in the loss of manufacturing jobs and wages, negatively affecting areas in the United States that relied on the manufacturing industry. Although the negative impact of Chinese import penetration on manufacturing employment is said to have largely diminished by 2012,[3] the sociopolitical consequences of the shock persist.

Summary

To understand how news media coverage of trade impacts public opinion, I focus specifically on U.S.-China trade relations from 2008 to 2018. This window of time encompasses many changes in the U.S.-China economic relationship, including several WTO disputes and tariffs imposed by both China and the United States, most recently resulting in a trade war. The identification of news media as an important communication actor in the flow of information about trade policy highlights the capacity for information in the public sphere to shape people’s opinions about foreign economic policy.

Chapter 2 brings together trade preference literature with political communication scholarship on how news media cover economic and foreign policy issues. In this chapter, I establish a set of hypotheses to test the relationship between the China shock, news coverage of U.S-.China trade, and public opinion about the local job market and the President. Chapter 3 explicates framing theory, focusing specifically on the concept of news frames. I also outline a liguistics-informed procedure for identifying and analyze issue frames in news that combines

[3] Scholars have noted that the trade shock persists in certain areas of the country, depending on that regions’ reliance on a specific industry (Setser, 2018).

manual validation with natural language processing and text-as-data techniques. Chapter 4 provides an overview of the data collection and methodology for this dissertation.

Moving into the results portion, Chapter 5 begins with the results of my framing analysis. In addition to describing each frame, I discuss variations in framing across state newspaper articles, national newspaper articles, and national broadcast programs. Chapter 6 lays out the results of the national-level model. Chapter 7 presents the results of the state-level model and highlights both the importance of state variation through a case analysis of three states (Wisconsin, Florida, and New Hampshire) and the role of national news media at the state-level. Finally, in Chapter 8, I discuss the implications of my findings for political communication, political economy, and foreign policy scholarship, focusing specifically on why national news coverage of U.S.-China trade may create incorrect interpretations of local economic trends.

Chapter 2: (National and Local) Trade, News, and Politics

Though the individual relationship between (1) economic circumstances and political attitudes, (2) economic trends and news coverage, and (3) news media and public opinion are well-studied, only a handful of studies have sought to consider how they collectively interact. In this dissertation, I argue that both trends in trade effects and news coverage of that trade, combined, help shape public opinion about the economy and politician, who are conventionally perceived as responsible for the economy (Rudolph, 2003).

There are several key reasons for emphasizing the role of traditional news media, even in an era of growing digital media consumption. With regards to reporting on foreign and economic information, traditional media continues to be essential sources (Aday, 2017; Damstra, Boukes, & Vliegenthart, 2018) and retain unique levels of access to political actors who make foreign policy or economic policy decisions. Compared to other journalists, economic journalists are also more likely to rely on traditional sources than Twitter and other social media platforms (Johnson, Paulssen & Van Aelst, 2018).[4] More broadly, political stories broken by traditional news outlets garner more attention than news broken by accounts in faster platforms, like social media (Harder, Sevenans & Van Aelst, 2017). Despite the importance of news media in shaping people's political and economic opinions, only a handful of studies have considered how trade preferences are informed by news media coverage (e.g., Hiscox, 2006; Guisinger, 2017), which may frame the effects of trade positively or negatively. This study therefore contributes to ongoing scholarship about public opinion and trade by combining trade preferences scholarship

[4] Despite the saying, "[On the internet] everyone is an expert on everything" (Guernsey, 2000), economic journalists admirably continue to rely on expert sources to contextualize the complex topic of the economy.

and political communication research about economic opinions to study how people understand the effects of trade.

One important factor that this dissertation considers is local and national variations in economic trends, news coverage of trade, and public opinion. This is essential for studying perceptions of trade, because trade effects often vary geographically (e.g., Autor, Dorn & Hanson, 2016)—one area can benefit from being able to export to a new market, while another may suffer from increased competition with international manufacturers. At the same time, however, citizens' news consumption and political attention has focused more on national politics and less on the local political economy (Hopkins, 2018). It is therefore unclear how these factors ultimately influence people's perception of the local economy and of national politics.

In this chapter, I outline the growing body of literature in political science, mass communication, economics, and sociology about trade, news, and public opinion, with a consideration of state-level variations and their possible obfuscation when focusing on the national political economy.

How do People Make Sense of Trade?

Though prevailing economic theory argues that trade benefits both countries, scholars have noted that the effects of increased trade between two or more countries have substantial intra-state variation (Hiscox, 2001; Fordham & Kleinberg, 2011). This is sometimes described as the "winners" and "losers" of international trade (Costa, Garred, & Pessoa, 2016). Winners of trade include export-competitive sectors and sectors with more abundance resources, whereas losers of trade encompass sectors with scarcer resources (for more on the Heckscher-Ohlin model, see O'Rourke, 2003).[5] Even in situations when trade is ideal for two countries in general, increased trade liberalization inevitably produces losers (Stolper & Samuelson, 1941).[6]

Scholars have unsurprisingly found that political attitudes and trade preferences are shaped by whether a person is a winner or loser of trade. Jobs that are highly routinized are considered easier to move overseas (more "offshorable"); consequently, people who hold such jobs are more likely to support protectionist policies (Owen & Johnston, 2017; Rho & Tomz, 2017). These attitudes shape voting behavior and elections in democracies (for a U.S. case, see Jensen et al., 2017; for a European case, see Colantone & Stranig, 2018a). In other words, even if trade is fair in general, losers of trade who constitute importing voting blocs may swing elections (Majlesi, Dorn & Hanson, 2016). Globalization has also been tied to increased support for left-wing and right-wing populism in different countries (Rodrik, 2018).

These considerations of trade effects are called egotropic trade attitudes—when people's perceptions of trade are influenced by trade's impact on the individual's pocketbook (Hearn, 2020). However, occupation alone does not explain trade preferences, especially since people do not necessarily understand how their own industry is impacted by global trade (Medrano & Braun, 2012). The alternative explanation, sociotropic preferences, posits that perceptions of the national economy as a whole alter people's trade preferences (Mansfield & Mutz, 2009; Colantone & Stanig, 2018b). Rather than focusing on personal benefits or losses, the sociotropic explanation argues that people consider the overall wellbeing of the national economy (Grafstein, 2009). Scholars have pointed to in-group and out-group identification (Mutz & Kim

[5] In economics, labor is a resource: sectors with cheaper labor are able to produce more labor-intensive goods.

[6] Some scholars note that losses as a result of trade liberalization are often temporary and do not offset the benefits gained from trade. Nevertheless, even minimal changes in the labor market can have substantive political consequences, such as motivating an economically disenfranchised group to vote.

2017) and patriotic or nationalist attitudes (O' Rourke, Sinnott, Richardson & Rodrik; Mutz, 2018) as contributing to skepticism about open trade. This appears to be mediated by geopolitics: who we trade with informs our perception of whether trade openness with that state is beneficial or detrimental to the domestic economy (Chen, Pevehouse, & Powers, 2018).

It is worth acknowledging that these two arguments are not necessarily in opposition. As Fordham and Kleinberg (2012) argue, there is likely a relationship between people's economic interests and their position in the national economy. Given that the effects of the China shock vary geographically, it is also possible that people's sociotropic attitudes are locally-focused rather than rather than nationally focused (Alkon, 2017). Despite this, many studies have continued to pit these two explanations against one another (e.g., Schaffer & Spilker, 2019; Jamal & Milner, 2019).

Trade Preferences and U.S. Politics

Trade has been an important political issue in the United States for as long as the country has existed. Historically, the United States was, "a country that wanted all the trade privileges of the imperial mercantile system without being a part of the system" (Wright, 1943, p. 176). The founding fathers used tariffs to protect domestic industries and generate revenue. From 1789 to the late 1800's, tariffs were almost always the largest individual source of income for the U.S. government (McGuire & Van Cott, 2002). But the 1930 Smoot-Hawley Tariff Act, signed by President Herbert Hoover, exacerbated the Great Depression by increasing the cost of over 20,000 goods, ending political and public support for protectionist policies. After World War II, the U.S. helped establish the current trade-liberalized international economic system, cementing its role as a global economic power.[7]

[7] Many agreements in the Bretton Woods Conference, including the establishment of the IMF, adoption of GATT, and the implicit determination of the U.S. dollar as the reserve currency, benefitted the United States' position in the

Current U.S. discourse about trade is grounded in these historical experiences. When terms such as "comparative advantage" or "protecting domestic industries" are used in the public sphere, they evoke culturally-relevant, historically-rooted belief system about how the United States should operate in the international economy. For example, when advocating for protectionist policies, politicians have used the term "fair trade," effectively implying that purely free trade can be "unfair," and that tariffs are a corrective action (Conti, 1995). Thus, discourse markers about trade are not novel, but they are applied to new contexts as a domestic economy (and its status in the international economic system) changes over time.

Despites its salience as an issue, trade has not generally been considered an issue with clear partisan positions.[8] In the past, espousing trade liberalization attitudes was a bipartisan endeavor (Eckes, 1995). However, in recent years, the two parties' positions on trade has fluctuated, likely as a result of 21st century globalization (Irwin, 2020). When politicians—both Democrats and Republicans—advocate for protectionism, the rationalize is often that policies such as tariffs protect jobs in domestic industries. There also seems to be the ulterior benefit of helping first-term Presidents electorally among certain demographics. The last three U.S. Presidents, George W. Bush, Barack Obama, and Donald Trump, all imposed tariffs in their first term in office, targeting industries whose workers constituted an important voting bloc.[9] In other words, partisan elites have varied in their position on trade liberalization over time.

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international economic system.

[8] Internationally, parties on the right tend to advocate more for open trade (Milner & Judkins, 2004).

[9] Bush's 2002 tariffs were placed on international steel, which is said to have benefitted him politically in steel-producing swing states like Pennsylvania, West Virginia, and Ohio (Tran, 2003). Obama's 2009 tariffs were placed on Chinese tires, in hopes of shoring up union support (James, 2007). As of January 2020, Trump has imposed tariffs on 16.8% of goods (as a share of all U.S. imports in 2017, see Congressional Budget Office, 2020). This follows his specific campaign promise to protect steelworkers' jobs (Rickard, 2018).

U.S. News Media Coverage of Foreign Economic Policy

Though economists have acknowledged the importance of journalists (e.g., Poole, 2004), a handful of studies in trade preference literature discuss media influences; even fewer empirically test its effects. Those that have tend to be critical of journalists (e.g., Jacob, Christandl, & Fetchenhauer), particularly for covering trade too negatively (this is similar to coverage of other foreign and economic policy issues, see Grafstein, 2009). For example, using a content analysis of nightly news from 1969 to 2012, Guisinger (2017) finds that coverage of trade is asymmetrically higher when trade deficits are higher, during trade surpluses, news hardly covered trade.[10] She also finds that news coverage tends to focus on imports far more than exports. By presenting the consequences of trade asymmetrically, people may develop a skewed perspective of the economy (Soroka, 2006). Focusing specifically on presidential approval, Burden and Mughan (2009) showed that, during the Clinton administration, media attention to a trade dispute against Japan amplified presidential disapproval, but the same did not occur during a dispute against Canada that was comparable in deficit but received significantly less media attention. They also found evidence that trade deficits increased presidential disapproval because of the perceived negative consequences of trade deficits on the domestic labor market.

In an experiment focusing on issue framing effects related to trade, Hiscox (2006) found that participants were more responsive to anti-trade issue frames compared to pro-trade issue frames, particularly among less-educated voters. It is worth noting, however, that the stimuli provided in this experiment were not news articles; rather, the interviewer read a sentence or two about trade. For example, the pro-trade stimulus was, "Many people believe that increasing trade with other nations creates jobs and allows Americans to buy more types of goods at lower

[10] This adheres to norms about newsworthiness—events that negatively impact society are considered more newsworthy and receive more media attention (Peterson, 1979; Trussler & Soroka, 2014).

prices."[11] While the use of snippets as stimuli is a popular practice in political science experiments to test issue framing, they lack external validity: this is not how an issue is framed in news (nor in political advertising, nor in political discourse, online or offline).

Regardless, these studies highlight the capacity for news media to shape people's perceptions about trade and show how news media norms can unintentionally skew coverage of trade. Given that news most often frames trade negatively and in terms of job loss and trade deficits, it is likely that this news coverage produces a negative and somewhat misleading understanding of trade, to the dismay of economists.

Local Areas and National News

State-level variation is of great interest to this dissertation because public opinion likely varies by the state of the economy and the news ecology. Previous work, particularly using individual-level public opinion data, has highlighted the importance of local context in shaping people's political and economic opinions (Ansolabehere, Meredith & Snowberg, 2014; Suk et al., 2020). However, the influences of economic trends on public attitudes or behavior appears to vary by geographic focus. Though some studies have found that retrospective economic voting—voting based on how the economy is doing—is nationally-focused (Morgenstern, Smith, & Trelles, 2017), others argue that it is local economic trends that shape people's attitudes at all political levels, and particularly politicians of the President's party (de Benedictis-Kessner & Warshaw, 2020). Of course, the two are also related—people's attitudes about the national economy can be shaped by local and state-level economic benchmarks such as unemployment (Books & Prysby, 1999). Furthermore, local governments may have substantially less control over how their local economy may be impacted by national trends (Warshaw, 2019).

[11] The anti-trade stimulus was, "Many people believe that increasing trade with other nations leads to job losses and exposes American producers to unfair competition."

The increasing nationalization of political attitudes and news media likely helps explain why national trends matter substantially to some voters. As U.S. politics becomes more nationally-focused (Hopkins, 2018)—exacerbated by the rise of local news deserts, or areas without local news coverage (Pickard, 2017)—it is likely that the news information people are consuming about the economy is nationally-focused. Most troublingly, studies have found that changes in media ownership are a driver of increasingly nationalized and polarized "local" news content (Martin & McCrain, 2019). The increasing nationalization of news specifically likely contributes to the growing focus on national, as opposed to local, economic trends.

The result of these dynamics is a complicated relationship between the local economy, the national economy, local news media, national news media, and public opinion. Importantly, how people use news to make sense of the local and national economy and politics are likely geographically heterogeneous (Gomez & Wilson, 2001)—no two states are likely to have the same relationships.

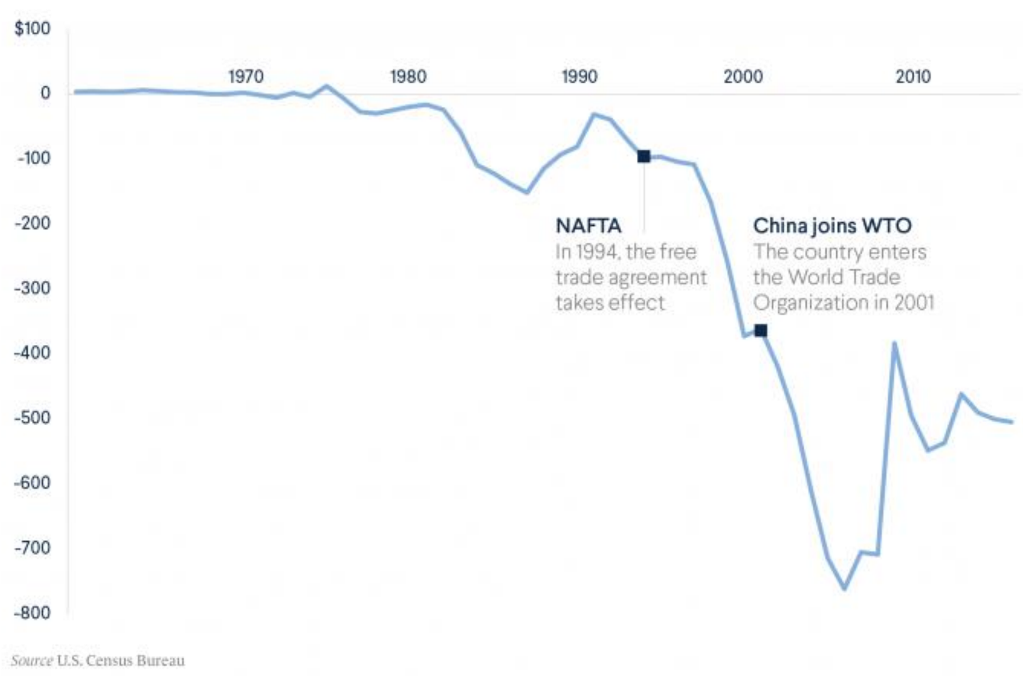
The China Shock in the United States

In 2001, China was admitted into the World Trade Organization WTO). To be admitted, China transformed its economy into an open market system by reducing its tariffs and increasing trade with other members of the WTO. China's inclusion in the WTO deepened their economic relationship with the United States. After this, the United States began importing Chinese goods at an increasing rate (U.S. Census Bureau, n.d.), resulting in an unprecedented trade deficit: U.S. citizens were buying far more Chinese goods than they were selling them to China. The size of the trade deficit led to a terms-of-trade shock (henceforth, "trade shock"),[12] or a "sudden, large,

[12] There are many different types of trade shocks, see Jääskelä & Smith (2013).

and enduring change[s] either in imports or export prices" (Funke, Granziera, & Imam, 2008, p. 3). Figure 1, from McBride & Chatzky (2019) illustrates the monumental size of this deficit.

Figure 1: U.S. Goods and Services Trade Balance, 1960-2016, in billions of USD (Source: McBride & Chatzky, 2019)



This specific shock, the China shock, most directly and negatively impacted manufacturing employment in the United States (Autor, Dorn & Hanson, 2016).[13] Because manufactured goods were cheaper to produce outside of the U.S., many of these jobs were offshored to China and other countries. In their study, Autor et al. (2016) emphasized the intra-country geographic variation of the China shock—Chinese import penetration most greatly impacted commuting zones with a higher number of manufacturing jobs.

To economists, those who lost manufacturing jobs were simply suffering from a short-term trade adjustment (Coughlin, 2002). Many also note that the average person does not think

[13] China shocks have also been found other areas, including Asia (Feenstra & Sasahara, 2018) and Europe (Dauth, Findeisen & Suedekum, 2014)

about the benefits gained from cheaper commodities or goods (Rho & Tomz, 2017).[14] But politically, people who lost manufacturing jobs can constitute an important voting bloc, especially in swing states (Stettner & Yudken, 2019). For them, the impact of the trade adjustment is not inconsequential; it is their livelihood.

The end of the China shock as studied by Autor et al. (2016) coincided with the 2008 Recession, further damaging manufacturing employment.[15] Though the economy recovered in the years following, the relatively slow growth and nearly consequence-free outcome on people who caused the recession left people disgruntled and in greater levels of economic insecurity (Savage, 2019; Hacker, Rehm, & Schlesinger, 2013). Compared to employment in other U.S. industries, the manufacturing sector has recovered the least from the recession (U.S. Bureau of Labor Statistics, 2018).

Consequences of the China Shock on Trade Preferences

Studies of the political consequences of the China trade shock vary in their findings. Majlesi, Dorn & Hanson (2020) showed that districts more greatly impacted by the China shock became more politically polarized, as Republican districts were more likely to vote in a conservative Republican, and Democratic districts were more likely to vote in a liberal Democrat. Other scholars have found that citizens vote out incumbents when the local economy is more greatly impacted by import penetration (Hellwig & Samuels, 2007).

The most popular sociotropic argument focuses on status loss, arguing that it was not the actual loss of manufacturing jobs, but the perceived loss of status as an economic superpower,

[14] Kemps (2007, p. 28) also notes this but argues that people value employment more than cheaper goods.

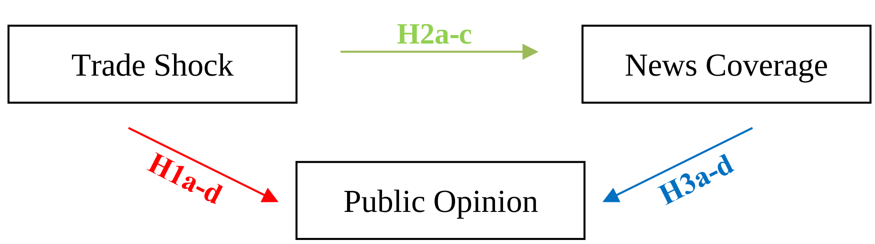
[15] It is important to note that the two are not directly related (the U.S. housing bubble burst that instigated the recession occurred independently of the China shock); however, the economic ills caused by the bubble burst compounded on the economic impact of the China shock.

that affected voting. Treating trade and immigration as status loss issues, Mutz (2018) found that perceptions of status loss influenced people's willingness to vote for Trump in the 2016 U.S. presidential election, even when people were not directly or community-wise affected by the loss of manufacturing jobs. Responding to Mutz (2018), Morgan (2018) argues that economic interests mattered as much as status threat—but to make this argument, he interprets trade as a material interest and not a status threat. In truth, it is both a status threat and a material interest: trade matters to people because having a high economic status internationally should benefit people in that country materially in the lifeworld.

Hypothesizing Relationships Between Trade, News Coverage, and Public Opinion

To test the relationship between the China Shock, news coverage, and public opinion, I propose the following model based on the aforementioned research discussed (Figure 2).

Figure 2: The Relationship between a Trade Shock, News Coverage, and Public Opinion



In the model, each box represents a group of variables, and each arrow represents a hypothesis.

The China Shock → Public Opinion

The first arrow suggests a relationship between the manufacturing job loss as a result of import penetration and public opinion of the local job market or of the President. If people in a state are more likely to be personally affected by the China shock, the egotropic argument would suggest that their perception of the local job market would decrease (Schaffer & Spilker, 2014). I therefore propose the following hypothesis:

> **H1a**: National manufacturing job loss as a result of import penetration from China (i.e., the China shock) will be related to more negative perceptions of the availability of local jobs.
>
> **H1b**: State-level manufacturing job loss as a result of import penetration from China (i.e., the China shock) will be related to more negative perceptions of the availability of local jobs.

Citizens also evaluate politicians on whether they are able to maintain a stable and steadily growing economy (Easaw, 2010). This is especially true of U.S. Presidents, who are credited or blamed for the state of the national economy as measured using metrics such as unemployment, wages, and inflation (Weatherford, 2012).[16] Because citizens also evaluate Presidents based on their international economic policy like trade (Berlemann & Enkelmann, 2014; Burden & Mughan, 2003), I hypothesize that the China shock will lower people's perceptions of presidential job performance.

> **H1c**: National manufacturing job loss as a result of import penetration from China (i.e., the China shock) will be related to more negative perceptions of the President's job performance.
>
> **H1d**: State-level job loss as a result of import penetration from China (i.e., the China shock) will be related to more negative perceptions of the President's job performance.

The China Shock → News Media

One responsibility of the press is to report on issues that matter to citizens (Vujnovic et al., 2010). This includes translating technical jargon into an understandable language (Miles & Morse, 2007). When simplifying highly specialized language to the layperson, journalists may

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[16] Though the Constitution gives Congress the right to levy taxes, Congress has since given the President substantial power to negotiate trade deals and impose tariffs (Tarullo, 1986)

rely on “processes of interpretation and selection” (Anderson, 1997, p. 53). This process can greatly benefit citizens. For example, if international events are covered in television news (and this is a big “if”), citizens have more knowledge of foreign affairs (Aalberg et al. 2013).

Given the complexities of economic information, it is not sufficient to simply report a statistic and assume the audience will understand what it means or why it is important to their lives. Instead, journalists must contextualize information about the economy to the public (Soroka, Stecula, & Wlezin, 2015; Kostadinova & Dimitrova, 2012). One way in which they do so is through news framing.

However, journalists take many considerations into account when constructing a news story, including how a story is newsworthy (Shoemaker & Reese, 2013). As Stimson (1991) notes, “Journalists pursue ‘news’ as a criterion of relevance. Change is news. Stability isn't't” (p. xxiii). Such norms about what constitute newsworthiness can present a skewed portrayal of reality. For example, news media asymmetrically cover the economy more during a downturn which, in turn, shapes public opinion (Soroka, 2006). Guisinger (2017) confirms this finding in the context of trade: on television, the negative consequences of trade are over-reported, and the positive consequences are under-reported.

Since news media emphasize negative economic phenomenon, I hypothesize that news media will produce more stories framing U.S.-China trade negatively if there is a China shock

> **H2a**: Manufacturing job loss as a result of import penetration from China will increase national newspaper articles framing U.S.-China trade as bad.
> **H2b**: Manufacturing job loss as a result of import penetration from China will increase national television programs framing U.S.-China trade as bad.
> **H2c**: Manufacturing job loss as a result of import penetration from China will increase state-level newspaper articles framing U.S.-China trade as bad.

Local and National News Media. Because the China shock varies by geographic region, it is worth considering the degree to which state news media report on the China shock's effect of their own state. On one hand, this seems logical: local news media should cover the local economy. On the other, recent trends in local journalism and local politics suggest that political issues have become highly nationalized (Hopkins, 2018). As a result, people may not know much about local politics or economic trends. This is exasperated by the loss of independently owned local journalism organizations (either by bankruptcy or being bought out by a national company) and the rise of corporate-owned news outlets that put profit over quality news.[17]

The nationalization of politics and political news can influence local news reporting about U.S.-China trade. In particular, state news media may be covering national economic trends as opposed to local trends. Studies have found that when local news organizations are bought out by national corporations (e.g., Lee Enterprises, Gannett, Alden Global Capital), the outlet's proportion of local news reporting decreases and is replaced by national news stories (Martin & McCrain, 2019). Local news organizations may also rely on news wires like the AP to report on international affairs such as U.S.-China trade. Given the possibility that local news outlets often publish national stories, I ask the following research question:

> **RQ1**: To what extent do state-level newspaper coverage of U.S.-China trade focus on national stories?

Such a finding would be troubling because trade and import penetration impacts different geographic parts of a country differently (Autor et al., 2016). People using national-level benchmarks, therefore, may not be accurately assessing their local economy.

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[17] A quintessential example of this is Alden Global Capital, which owns 12 of the newspaper in the corpus. Alden Global is infamous for "hacking and slashing" newsroom jobs once they buy a newspaper (e.g., Hutchins, 2018). While this might increase the fiscal "efficiency" of news reporting, it comes at the cost of quality local reporting.

It is worth acknowledging that this dissertation focuses on the level of the U.S. state as "local," but it is possible to have more granular analyses of regional economies (Autor et al., 2016, for example, studies commuting zones). In terms of data accessibility, there is a tradeoff between geographic granularity and temporal granularity: more specific geographic data (e.g., commuting zones) is reported in more aggregated time units (e.g., years). My decision to focus on state data at the monthly-level balances the geographic-temporal data tradeoff.

News Media → Public Opinion

The last group of hypotheses addresses news media's influence on public opinion. As synthesizers of information, news media help people make sense of economic issues, potentially influencing their attitudes about the economy or the President. However, news media coverage is rarely a perfect representation of reality, particularly with regards to the economy (Guisinger, 2017; Hiscox, 2006; Soroka, 2006). This suggests that news media may have an influence on public opinion independent of the China shock. Given news media's tendency to focus on negative economic trends as opposed to positive ones, I hypothesize that negative framing of U.S.-China trade will decrease people's people opinion of the health of the economy.

> **H3a**: Negative news coverage of U.S. China trade will be related to more negative perceptions of local jobs available.
>
> **H3b**: Negative news coverage of U.S.-China trade will be related to lower perceptions of the President's job performance.

Additionally, as people rely more on national news outlets as opposed to local ones (Wadbring & Bergström. 2017), it is also possible that public opinion is more greatly influenced by national news media, not local news media. I therefore hypothesize national news framing influences people's perception.[18]

> **H3c**: National news coverage of U.S. China trade is related to people's perception of the health of their local economy.
>
> **H3d**: National news coverage of U.S.-China trade is related to people's perception of Presidential job performance.

Differences in public opinion by partisanship. There are some issues where political ideology determines the use of different frames (e.g., abortion, healthcare, taxes). Trade is not typically one of them. For example, both Republicans and Democrat politicians have employed protectionist policies. Nevertheless, there are possible differences in partisanship, especially given that Republicans are attentive to job creation (Schake, 2016). I therefore ask the following research question:

> **RQ2**: To what extent do the influences shaping Republicans' public opinion of the economy and the President vary from the influences shaping Democrats' public opinion?

Relationships, not Effect Sizes

It is worth emphasizing that the point of this dissertation is not to study the relative power of the China shock and news media. Instead, the goal of this dissertation is to illustrate that the geographic variance of economic factors *combined* with the increasing nationalization of news work together to shape public opinion about the economy and of the President.

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[18] I anticipate that the directionality of public opinion will be contingent on the frames used.

Chapter 3: A Linguistic Approach to Framing Theory

In this chapter, I will explore what framing is and explain how framing theory can illuminate our understanding of news coverage about U.S.-China trade.

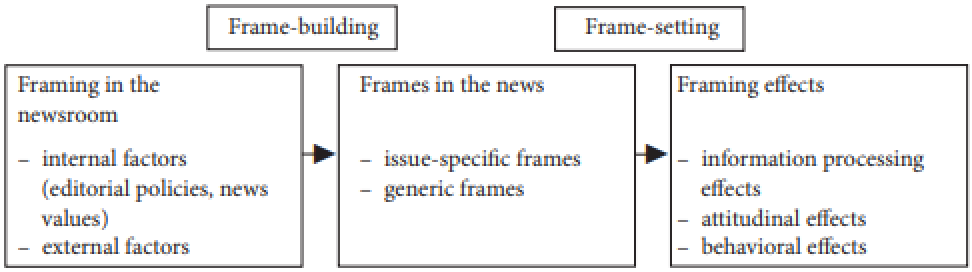
Framing Theory

Most papers on framing theory begin with a discussion of how communication scholars have struggled to concretely conceptualize or define framing (see Borah, 2011; D'Angelo, 2002; Scheufele, 1999). When arguing that framing is a "fractured paradigm," Entman (1993) attributes the fractured nature to framing theory's interdisciplinary origins, primarily from sociology and psychology scholarship. Since then, scholars have aspired to define, conceptualize, and operationalize "frames" and "framing" to answer different questions about how communicated information is presented and what effects that communication has on people individually or on society as a whole.

At the heart of framing theory is a model of the framing process (see Figure 3). The framing process has two parts: frame building and frame setting. This two-step procedure is generally agreed upon in the scholarly canon (Chong & Druckman, 2011; de Vreese, 2005; D'Angelo, 2002; Entman, 1993; 2003; Gamson & Modigliani, 1987; Iyengar, 1990; Scheufele, 1999). First, people produce frames through "frame-building." Audiences then consume these frames by reading, watching, or listening to the news, which results in "frame-setting." For the remainder of the dissertation, I will refer to "frame-setting" as producing "framing effects" (attitudinal or behavioral consequences based on consuming framed content).[19]

[19] I use the term "framing effect" because "frame-setting" has been used in too many different contexts. For example, Bruggermann (2014) uses "frame setting" to describe a type of "frame building" process. Furthermore, the term "framing effects" is commonly used in this literature (see Borah, 2011; Chong & Druckman, 2011).

Figure 3: An Integrated Process Model of Framing (de Vreese, 2005)[20]



What passes in between these processes are "frames," which de Vreese defines as a "central organizing package" (de Vreese, 2005, p. 53). De Vreese identifies two types of frames: issue-specific frames (like the ones studied in this dissertation) and generic frames (which can be applied across multiple issues). However, what constitutes an "organizing package" is unclear in this definition.

Given that the framing process hinges in part on what news frames are and whether they have effects, much scholarly effort has been devoted to their conceptualization. Often, however, scholars often define frames based on what they do, rather than what they look like (Matthes, 2009). Citing Tuchman (1983), Chong and Druckman (2007) argue, "A frame in communication 'organizes everyday reality'" (p. 106). Other studies quote Entman's (1993) now-famous definition, "to frame is to select some aspect of a perceived reality and make them salient in a communicating text in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (p. 52).[21] While absolutely important, this definition is incomplete. Intent or effect is only half the equation—we should also know what a frame looks like.

[20] de Vreese is not the first to propose this, but his model's simplicity pares down framing to its essential components.

[21] This definition actually uses "frame" as a verb ("to frame") but it is nevertheless used to identify frames (n.)

Abandoning frame building almost completely, Cacciatore, Scheufele & Iyengar (2016) argue that framing theory should focus primarily on media effects (p. 9), especially as a way of limiting what constitutes a frame. For example, the authors contend that emphasis-based manipulated should not be considered in framing theory. Scheufele and Iyengar (2012) make a similar argument, encouraging scholars to study equivalency frames, not emphasis frames, to avoid confounded definitions. The benefit of this approach is the ability to manipulate frames in experiments. However, this conceptualization also severely limits the scope of framing research and overemphasizes framing effects scholarship at the cost of understanding the sociological construction of these frames. Furthermore, and more importantly, it lacks external validity—information is rarely presented using equivalency frames (Druckman, 2001). They may make experiments easier to perform, but what use are framing effects identified in experiments if the stimuli used does not exist often in the real world?[22]

Setting aside the tautological issues of defining frames by their effects, these definitions do not clarify what is or is not a frame. Why is it so difficult to isolate frames from there communication context to study framing?

I argue that one reason for this difficulty is that the process, *framing*, is conflated conceptually with the product, *frames* (Vliegenthart & van Zoonen, 2011). In reality, framing does not produce "frames" per se, but framed communication, because the product of "framing" (the process) cannot be disentangled from the message as a whole. To study the consequences of frame building or to test framing effects, scholars must isolate and study communication patterns that serve some sort of discursive function. Importantly, the process of identifying such patterns

[22] A focus on effects would also likely produce a survivorship bias in framing research, particularly given the difficulty of publishing null findings. In other words, communication scholars would only study frames with effects, and would be less likely to understand the conditions under which frames are or are not effective (Vliegenthart & Van Zoonen, 2011).

is inherently reductive. In other words, “frames” are an analytical and conceptual tool to help scholars study framing, not the actual product of framing.

De-Nominalizing “the Frame”

Frames are how researchers operationalize framed communication—a way for us to empirically isolate the pervasive, manifest communication patterns that produce framing effects (in this dissertation, I focus on linguistic communication). A frame is only real insofar as a researcher has found it useful to study how an issue or topic. From this perspective, the sociological and psychological approaches to framing are still important. However, the term “frame” is not defined by either process. Instead, it is defined by the researcher,[23] who must both curate the communication patterns representing a frame and contextualize its use. Researchers can operationalize a variety of different frames from a corpus by identifying linguistic, auditory, or visual patterns.

To understand this conceptualization of frames and how it fits into the broader framing research agenda, it is necessary to understand not just the term “frame,” but also its related terms: “to frame” (verb), “framed” (adjective), and “framing devices” (noun).

I define the *verb* **to frame** as the entire framing process model, including frame building and frame setting (de Vreese, 2005). This model can be conceptualized as a recursive loop (see Scheufele, 1999), though that is not a prerequisite. **Framing actors** are people who have the capacity to engage in the frame building process; this includes (but is not limited to) journalists and political-and-economic elites (Brüggemann, 2014). When a framing actor frames a news story, this produces **framed** (*adjective*) **communication**. In this noun phrase, “framed” is a descriptor for the content. Thus, “framed” (the adjective) cannot be divorced from the message.

[23] “The researcher” refers to the generic researcher, not me (the person writing this dissertation).

If one were to take a broad approach to framing, all natural language communication could be considered framed (since all interlocuters have communication goals). From this perspective, framed content can be studied with a variety of theoretical perspectives, including rhetoric and conventional discourses (Strauss, 2012; Kuypers, 2009). However, in this dissertation, I will focus specifically on **news framing**, which is constrained by professional and journalistic writing norms (D'Angelo & Shaw, 2018).

Within framed content are **framing devices** (Pan & Kosicki, 1993; D'Angelo, 2002). Framing devices (noun) are manifest features of text or audio-visuals that shape, inform, or influence discourse (Capella & Jamieson, 1997). Examples include the use of keywords, metaphors, and analogies (Burgers, Konjin & Steen, 2016). For example, an article about abortion framed in the context of "protect[ing] human life before birth" will use different language compared to an abortion article framed in terms of women's "right to control one's own body" (see Ferree, Gamson, Gerhards & Rucht, 2002). The two articles would likely rely on different keywords (e.g., fetus vs. human life), use different sources, and portray relevant actors differently (e.g., politicians, abortion doctors, women who have abortions).[24]

Framing devices can appear in many parts of a news story; Tankard (2001) identifies 11 framing mechanisms, or places where frame devices can appear.[25] When embedded in language, framing devices vary in size. For example, McLeod and Shah (2015) identify four sizes of framing devices (which they call message frames): cues (like keywords), statements, arguments, and packages (article-level frames) (p. 26). These levels represent a linguistic "scaling-up" from words into sentences, sentences into claims, and claims into narratives.

[24] Second-level agenda setting literature describes these actors as "stakeholders."

[25] He calls these the "focal points for identifying framing" (p. 100).

Finally, we come to **the frame**, which is a researcher-defined set of overt framing devices that approximate framed communication. The researcher is responsible for determining the scope of the frame, the framing devices that collectively constitute the frame, and the intended function of the frame. As I have mentioned, frames are analytical tools. A scholar cannot point to a news article and declare, “behold, I have found a frame!” They can only identify frame devices and make the argument that they occur together.

Scholars should be able to tie the use of these frames to its communicative function (Borah, 2011); this is where scholarship on what a frame does is essential. For example, several framing devices can collectively serve two or more of Entman’s (1993) functions of a frame. Or, scholars can show that multiple framing devices achieve one of Snow et al.’s (1986) frame alignment processes. The function determines the appearance of the frame in language form. Therefore, isolating language patterns that serve a communicative function can help scholars study the framing process.

The majority of communication research about framing utilizes content analyses to identify frames (Borah, 2011). Unsurprisingly, this scholarship has found a wide range of frames. For example, equivalency frames convey information in terms of risks options (a benefit of studying these frames is that risks can be re-framed as gains or losses). Emphasis frames make some pieces of information more salient than others (D’Angelo, 2017). Scholars have also identified episodic and thematic frames (Aarøe, 2011), generic frames (de Vreese, 2005), and conflict frames (Schweitzer & DeChnrch, 2001), which have been used to study many news stories and political issues. I do not believe the variety of frames studied is a limitation of framing scholarship—in fact, I argue it is an asset: the variety of frames simply reflects the variety of ways in which humans use language and other communication systems to convey information.

Using Computational Linguistics to Study Framed Communication

This dissertation takes a computational linguistic approach to studying frames.[26] Natural language processing provides new ways to study linguistic news framing in large corpora (just as computer vision has benefited visual framing research). This is especially important in the modern media system, where people have produced more linguistic content than ever before. Given the unprecedented amount of communication data that now exists, it is no wonder that political communication scholars have turned to computational methods and tools.

Before we dive into what computational methods can do for language analysis, let me begin by explaining what computational methods cannot do. Language is *rich*. One utterance has a plethora of information. Qualitative analyses, because of their emphasis on analytical depth, afford us a complex analysis of language (e.g., Wodak, 2006; Gal, 1989). Quantitative and computational methods cannot replicate that richness. Transforming language into numbers is a reductive process. Instead, the strength of these methods lies in being able to isolate linguistic features in large corpora and test the effects of those features (Grimmer & Stewart, 2013).

The sacrifice of depth for breath is only valuable if the researcher processes language appropriately for their research question. In other words: researchers should not process language to the point where they can no longer answer their research question. Similarly, if researchers are not considering the appropriate combination of language features, the measure they construct may not accurately capture the framing phenomenon they want to study.

[26] Some would describe this approach as a text-as-data (Grimmer & Stewart 2013) or an algorithmic text analysis (Lacy, Watson, Riffe, and Lovejoy, 2015) approach. While these terms are useful, I argue that computational linguistics—using computational and algorithmic methods to study language—is a more suitable description, as this is a paper about how text analysis should be informed by linguistic theory and not just computational ease.

Thus, computational methods do not substitute other methods; instead, they are harmonious. Natural language processing cannot replace what a scholar does, and computational methods are more effective in tandem with human interpretation. These methods require deep, extended interaction between a scholar and her code. The trust a scholar has for her computer-assistant results is developed over a long period of time, as she learns how to use different algorithms, methods, or applications. However, in learning these methods, the researcher is able to analyze language data at an unprecedented scale.

Traditional natural language processing (NLP) follows five steps: (1) collect a corpus (e.g., via scraping or an API), (2) clean and "process" the corpus, (3) analyze the corpus with a computational technique (e.g., dictionary analysis), (4) validate the method, and (5) present the results. Below, I focus on important considerations at the second and third step, processing and analyzing text data.

Processing Text for NLP

To use natural language processing tools, a corpus (a collection of written language) must often be altered. Processing ("wrangling") manipulates language data, often by annotating or removing layers of natural language. This reduces a corpus into its most meaningful components for a study. The goal of processing is to transform the language data into a structure that can be read and understood by a computer algorithm. This step is often overlooked; however, processing can greatly influence one's analysis (Grimmer & Stewart, 2013).

Language processing can occur at four levels: phonological, morphological, lexical, and syntactic (Muysken, 2013). Phonology focuses on speech sounds as the smallest unit of language. Morphology focuses on how combinations of speech constitute words. Lexemes refers to units of meaning encapsulated in one or a few words; a collection of lexemes for a language is called a lexicon. Scholarship about syntax will study how words are combined into phrases and sentences. Researchers can combine or isolate layers to operationalize social or psychological communicative phenomena emotive. This categorization is analytical, not empirical; in reality, these layers work together to construct language (Edelman, 1979). However, it can be useful to disaggregate linguistic features to study components individually before understanding how they work together (Ragin, 2014).

When processing, researchers rely on a programming language to tell computers how to handle language. If the researcher tells the computer to disregard a linguistic layer, the researcher is assuming that the layer has no meaningful information. For example, an analysis of the top keywords in a corpus does not need syntax; therefore, a researcher may simplify their corpus by removing its word order. This reduction must be intentional—arbitrarily removing language layers can severely harm the analysis. A researcher can also annotate language, illuminating meaningful patterns. Annotations are additive: they help the computer account for grammar and other language norms (e.g., the subject and predicate of a sentence or the use of an accent's features). Good annotations can greatly improve NLP tasks (Sennrich, Haddow, & Birch, 2016; Carmel, Mejer, Pinter & Szpektor, 2014). But producing them can be time-consuming, especially for large corpora.

Table 1 displays the computational processes for adding or reducing political language layers. From these layers, researchers isolate linguistic features: a manifest language form that, whether individually or as part of a set, represents or produces social or psychological phenomena (e.g. Gordon, 2008; Talmy, 1988; Bohner, 2001).

Table 1: Linguistic Layers of Computational Political Language Processing

	Reductive	Additive	Unit of Analysis
Phonological	Text / Transcript	Pitch, Tone, Prosody Notation	Phoneme
Morphological	Lemmatization	POS Tagging	Morpheme
Lexical (Semantic)	(Stop Words)	Tokenizing, Word Lists	Word/Lemma
Syntactic	Bag of Words	Dependency, Clausal Analysis, Word Embeddings*	Sentence

* Word embeddings are not a full annotation of syntax, but it does retain critical word-order information.

honological. Phonology is interested in how a message is uttered. Sensibly, it is primarily interested in spoken language, not written. Phonological analyses focus on features like accents, prosody, pronunciation, or tone (e.g., Purnell, Raimy & Salmons, 2009). Phonology can reveal how tone affects political discourse (Wilson, 2003**)**. For example, Bucy et al. (2019) used human-coded features of visuals, tone, and language to study how candidates' rhetoric during the 2016 U.S. presidential debate impacted social media responses. Another useful area of computational and phonological research is signal processing, particularly for studying speech perception and comprehension (Zhang, Xi, Xu, Shu, Wang & Li, 2011).

A study of language without phonology is, in effect, a study of text. The text-as-data method in political science (Grimmer & Stewart, 2013), for example, is primarily interested in written communication (e.g., speeches would be analyzed as transcripts).

Morphological. Studies of morphology n political language are interested in how words are constructed, including the use of different stem words, prefixes, and suffixes. Morphological features can have important semantic differences. For example, U.S. Republicans believe in "democracy," but do not identify as "Democrats," even though democracy and Democrat are part of the same lexeme. A lexeme is an array of possible conjugations and is represented by the root word (or "lemma"). The lemma "democra" represents a lexeme that includes {democracy, democratic, democrat} (words within a lemma are encased in braces "{}").[27]

Morphemes (e.g., suffixes, lexemes) can matter a great deal to political language. Morphemes are "micro-structures of different ideologies" (Freeden, 2013, p. 118). For example, the morpheme "libera" originates from the Latin word "liber," meaning *free*. Because of this, morphemes carry the historical weight of current and past societies. Even within one political philosophy, a lemma can be reshaped to serve many communicative goals (Jun, 2018).

When computational researchers account for morphology, it is typically to serve a broader goal like improving syntactic or semantic NLP tasks (Ogrodniczuk & Kopeć, 2017). However, it is more common to discard morphology with tools like stemming and lemmatizing. Stemming, which removes suffixes, cannot identify more morphologically complex lemmas (e.g., "thinks" and "thinking" are easy to stem, but "thought" is not). Lemmatizing is more advanced and considers a greater variety of conjugations. Both can be useful if the scholar is interested in concepts but not inflections. For example, in topic modeling, the distinction between "immigrant", "immigration" and "immigrating" may not matter.

Lexical. An analysis at the lexical level focuses on words. Because researchers are especially interested in the meaning of words, lexical analyses are informed by scholarship in semantics. A lexicon is a dictionary of words used in a specific language context.[28]

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[27] This is different from the computer science use of the word "lexeme", which is synonymous with the colloquial "word." A lexeme in tokenization research is any sequence of characters that match a token pattern (Aho, Lam, Sethi & Ullman 2007). For number tokens, the character sequences "42" and "3.14" are two example lexemes. To prevent confusion, I will not use this NLP definition of the term.

[28] Though "lexicon" is typically applied to language variations, like standard English (Bouguraev, Briscoe, Carroll, Carter, & Grover, 1987) or African-American English (Smitherman, 1998), researchers have also used lexicons for specific topics, like climate change (Maunder, 2012) or the medical field (Dunglison, 1874).

A preponderance of political language research focuses on this layer. This is justifiable—words are the bread and butter of language systems. Most NLP strategies account for words by tokenizing: when the researcher tells the computer to treat a document as a sequence of "tokens" identifiable by a common pattern. Word tokens are separated by a space and sentence tokens are separated with specific punctuation marks (exclamation marks, periods, and question marks). Word tokenizing is a de facto consideration of the lexical level.

Not all words in a lexicon are equally useful. For example, function words like pronouns (e.g., I, he) and prepositions (e.g., with, over) can embed valuable information, such as the affective state of the speaker (Pennebaker, 2011). But when identifying topics in a document, function words may not contain meaningful information. One way to disregard these words is to use a stopword list (Kanakaraj & Guddeti, 2015), which tells the computer to disregard certain words. To focus on words that are important to a research questions, scholars use keywords. Dictionary-based NLP strategies use lists of keywords ("dictionaries") to extract variables of interest from text document (Muddiman, McGregor & Stroud, 2019).

Syntactic. Finally, we reach the syntactic layer, where the semantic meanings of individual words are combined into comprehensible language. Syntax and lexicon are deeply related; without a lexicon, syntax would not have anything to organize and without syntax, a lexicon would be a jumble of words. Syntax can drastically change semantics; for example, the phrase "dog bites man" is different from "man bites dog."

Syntax parsing is a popular NLP task that annotates words by their syntactic attributes. [29] Advances in machine learning and word embedding have improved the accuracy of syntax

[29] To note: there are also syntax parsers for data languages, which help researchers extract information from a computer language, such as HTML. That is *not* what is being discussed in this dissertation.

parsers (Chen & Manning, 2014; Lee, Surdeanu & Jurafsky, 2017).[30] Annotating syntactic information can improve semantic classification (Zou, Tang, Xie & Liu, 2015), contributes to semantic network analyses (Van Atteveldt, Kleinnijenhuis & Ruigrok, 2008), and is essential for entity-based association: tagging descriptions to specific actors (Fogel-Dror, Shenhav, Sheafer & Van Atteveldt, 2019). Often, however, syntactic information is processed out, most commonly by "bag-of-words" processing (Grimmer & Stewart, 2013), which reduces a document into a list of words and their frequency of use. Bag-of-words is a popular processing method because of its simplicity. For some tasks, such as word categorization, a bag-of-words strategy produces roughly the same quality of results as a syntax-considerate strategy would (Van de Cruys, 2008).

One way in which syntactic information can be partially retained is through word embeddings (Andreas & Klein, 2014). In this strategy, words are mapped in a vector space based on their similarity to one another. This processing method is informed by the concept of distributional semantic: that a word is known by the company it keeps (Lenci, 2008). Word embeddings have been shown to greatly improve NLP tasks (Levy, Goldberg & Dagan, 2015); however, they produce a large carbon footprint (Strubell, Ganesh, and McCallum, 2019).

Extracting Frames from Text with NLP

Once the data has been processed, researchers can apply computational techniques to extract information from text. This is useful to operationalize social science variables. NLP can detect events in news (Nguyen & Grishman, 2015), identify sentiment (Fang & Zhan, 2015) or deception (Rubin, Chen & Conroy, 2015), and analyze language change over time (van Aggelen,

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[30] There are two approaches to computationally interpreting syntax: head-driven phrase-structure grammar (Miyao, Ninomiya & Tsujii, 2004) and dependency grammar (Li, Cheng, Liu & Keller, 2019); this aligns with the two dominant grammar theories. Dependency parsing has become increasingly popular because of its ability to handle languages with free word order such as Hindi (Bharati, Husain, Misra & Sangal, 2009; Jurafsky and Martin, 2009). Dependency relationships have been aggregated to analyze clauses.

Hollink, & van Ossenbruggen, 2016). Programs such as Wordsmith or LIWC make it easier for non-coders to use computational methods (Touri & Koteyko, 2015). Though NLP in communication research has mostly focused on lexicon (e.g, McShane, Nirenburg & Beale, 2005), a handful of studies have highlighted the value of syntax, grammar, and closed-class words (e.g., van Atteveldt, Kleinnijenhuis & Ruigrok, 2008).

Variables can be extracted from language using text classification. Text classification refers to the process of using computational methods to tag or label messages (or "documents"). For example, social media accounts could be classified into "bot or human" (Chu, Gianvecchio, Wang & Jajodia, 2012), news articles into different topics (Roberts, Stewart, & Tingley, 2014), or messages into political ideology (Karamshuk, Lokot, Pryymak & Sastry, 2016).

Computational methods, and text classification in particular, have the potential to significantly advance framing analyses. Scholars have used a variety of computational techniques to identify frames, from counts of word co-occurrences (Lind & Salo, 2002) to supervised machine learning algorithms that learn from human-labeled data (Grimmer & Stewart, 2013). However, as I have previously discussed, a language pattern should be attributable to a framing function—not every language pattern is inherently a frame, and human interpretation is essential to connecting a language pattern to its frame function.

In line with this logic, I argue that unsupervised computational strategies are not very useful on their own for identifying frames (van Atteveldt, Welbers, Jacobi, & Vliegenthart, 2014). Though they can help in the exploratory phase of analysis, such as to direct our attention to meaningful keywords, the lack of human involvement is a detriment to identifying what language features carry situational, social or psychological meaning.[31] Semi-supervised

[31] Unfortunately, due to their ease of use, unsupervised methods are often used to identify frames (e.g., Kwon, Chadha & Wang, 2019; van der Meer, 2016). This obfuscates the difference between topics (identified by the

approaches (sometimes called "hybrid" approaches, see Lewis, Zamith & Hermida, 2013) and supervised approaches involving humans are more useful for operationalizing frames.

Because framed content is subtle and can vary in size (McLeod & Shah, 2015), researchers can employ different strategies to extract linguistic patterns at various levels. Table 2 presents the different levels of framing devices (from smallest, at the word-level, to the largest, at the document-level).

Table 2: Linguistic Layers of Message Frames for Computational Analysis

Frame Levels[1]	**Linguistic size**	**NLP Tasks**[2]
Cues *(concept frames)*	Word	Lexical dictionaries Supervised ML on tokenized corpus
Statements *(assertion frames)*	Clause/Sentence	Lexico-syntactic dictionaries Syntax triplets (subject-verb-object) Supervised ML on syntax-annotated corpus
Arguments *(thematic frames)*	2+ Sentences/Paragraph	Lexico-syntactic dictionaries Quote Analysis Paragraph Comprehension
Packages *(story frames)*	Document	Thematic + Statement + Cue Combinations Narrative analysis

[1] From Shah and McLeod (2015)
[2] Tasks used in this dissertation are highlighted. Although I account for the source of quotes, I do not analyze the quotes themselves.

Let's explore these levels in more detail.

Cues. Cues, or concept frames, refers to the use of individual words or phrases (e.g., "a partisan argument" is a noun phrase with an article, an adjective, and a noun). Because they are the smallest framing devices, they are simpler to identify than the other levels. The easiest way to analyze cues is through dictionaries: counting the use of keywords or n-grams in a document or

frequency of words) and frames (language patterns that are historically, culturally, or socially grounded and can have social or psychological effects). While I myself perform a topic modeling in my preliminary analysis, the results highlight limitations with using unsupervised methods on corpora with multiple media (see Appendix F).

corpus (e.g., Luther & Miller, 2005). Owing to the field's historical use of content analyses, dictionary analyses are quote popular in political communication (Muddiman, McGregor, & Stroud, 2019). One recent trend in dictionary analyses is the use of multi-lingual dictionaries (e.g., Lind, Eberl, Hidenreich & Boomgaarden, 2019).

Other strategies utilize algorithms to understand how words (cue frames) co-occur; this includes analyzing processed corpora (like document-term matrices) through supervised machine learning techniques (e.g., Cheeks, Stephien, Wald & Gaffar, 2016; Kananovich, 2018). For example, Burscher, et al. (2014) used an ensemble machine learning strategy to identify four generic frames: conflict, economic consequences, human-interest, and morality. Focusing on the case of earthquakes caused by gas drilling, Opperhuizen et al. (2019) employed a qualitative-to-quantitative process to inductively identify frames, operationalize them into quantitative measures, and use supervised machine learning algorithms to "scale up."

Statements. Cue framing devices are organized into assertions using grammatical rules about syntax, which typically spans the length of a clause or sentence. For a computer to understand how words relate to one another in a sentence, we need to provide it information about word order and syntax. As mentioned above, this can be done by annotating the corpus with syntactic information (e.g., part of speech information and dependency relationships).

While syntax considerations have been applied to a wide variety of NLP tasks, including semantic network analyses (van Atteveldt et al., 2008) and sentiment analysis (Cui, Shi & Chen, 2016), only a handful of studies on framing in communication scholarship have accounted for sentence structure. Scholar most commonly study sentences when seeking to understand how specific actors are described in language. For example, Van Atteveldt et al., (2013) operationalized framing by using syntactic information in their semantic network analysis to extract relationships between actors and issues. Another common strategy when studying English text relies on a sentences' subject-verb-object structure (e.g., Alashri et al., 2016). To study media bias, Hamborg et al. (2019) used a syntax-informed approach to extract the relationships between entities in news stories. They also focused on verbs that signal positive or negative sentiment.

Argument. Statement framing devices can be grouped to convey arguments, or "thematic frames." Thematic frames make some claim about a perceived reality, often relying on multiple assertions (McLeod & Shah, 2009). In terms of size, this level is the most ambiguous, ranging from two sentences to several paragraphs. One influential factor of an argument's size may be the media platform or genre; for example, written news and government documents construct arguments differently from social media messages. Domain-specific NLP methods may therefore be useful when identifying argument frames.[32] In the context of news frames, argument-level frames can include news features that are longer than one sentence, like anecdotes and quotes. Another way to think about frames is to consider how sentences are coupled together. For example, Eckle, Kluge, and Gurevych (2015) used a "claim-premise" argument structure to study news discourse. They find that the average claim was about one sentence long, and the average premise about two sentences.

Story Frame. Finally, people use multiple sizes of framing devices to package a narrative or story frames of a message. As previously noted, the language form of a message is greatly informed by its register and genre. For example, sentences in broadcast news tend to be shorter compared to written news (Oktavianti & Ardianti, 2019). One way to identify story frames is to aggregate smaller framing devices that collectively contribute to a story frame for a specific

[32] In natural language processing, a domain is a subject matter. Examples of domains include topical domains (e.g., messages about cancer) and genre/medium domains (e.g., broadcast news writing, tweets, Amazon reviews).

register. However, this must be done with genre structure in mind. For example, owing to the inverted pyramid structure norm in U.S. journalism, lead sentences carry more information and significance than sentences at the end of a news article (Park, Kang, Chung, & Song, 2012). Frame analyses studying story frames should take these genre norms into the account (Boon & Bimbaum, 2019).

Aggregating News Frame Layers

Most frame analyses utilize message-level variables. Aggregation is therefore essential to using NLP tools for framing analyses. It is here where the human interpretation is particularly influential: computers do not have prior knowledge about society or language patterns that would allow it to operationalize frames unless taught otherwise. Even when a machine learning algorithm is used, the quality of the algorithm is contingent on the quality of the data it learns on.

There are many techniques to aggregate lower-level framing devices into higher ones. The most common strategy involves counting framing devices. While simple, these strategies should not be overlooked, as they can produced results that parallel or even outperform more advanced methods (Zhang et al., 2019). Other relatively simple strategies include constructing an index or average (e.g., Khalifa, Nasser, & Alkhateeb, 2018; Serrano, 2017).

Supervised machine learning for text classification implicitly involves aggregation. But rather than having humans decide which keywords are valuable, humans rely on a machine to learn what keywords are meaningful based on human-labeled data. Supervised machine learning can identify linguistic patterns that would otherwise go unnoticed by the human eye (Burscher et al., 2014; Boumans & Trilling, 2016). However, a quality supervised machine learning strategy is contingent on quality training data.

Another strategy is to account for how different layers combine to follow social conventions about language use (i.e., grammar and genre norms). This method is less common because it requires the machine to understand how words become sentences, sentences become paragraphs, and paragraphs become narratives. However, as researchers advanced NLP, these strategies will likely become more accessible. For example, Hamborg et al. (2014) uses POS-tagging and other processing techniques to isolate candidates' names and align co-referenced nouns. The researchers then studied the noun's relation to frame properties (e.g., emotion, polarity, and honesty). To aggregate to these assertions, the researchers recommends using clustering techniques (though they themselves do not apply this method).

It is important to emphasize again that the goal of aggregating smaller framing devices is to create variables at the document-level (i.e., story frames). However, aggregation does not mean that studies using NLP should adhere to the one-article-one-frame pattern that has plagued other framing studies (Shah, Kwak, Schmierbach & Zubric, 2004). In fact, because NLP techniques allow framing scholars to study framed language patterns across a range of linguistic units, computational methods may be especially useful for advancing scholarship about how frames are used conjointly in one message.

Register Variations in Framing by Medium

Most frame analyses focus on one medium (e.g., Lück, Wessler, Wozniak, & Lycarião, 2018) or treat content from different media as collectively one corpus (e.g., Johnston, Friedman, & Sobel, 2015). This obscures the fact that the framing process (specifically, frame building: how journalists write framed messages) varies by medium. How someone would frame an issue in print is different from how someone would frame an issue on Twitter or in a broadcast story. In other words, two pieces of framed communication can convey a similar interpretation of an issue but look different because they were produced for different media. In sociolinguistics, differences in language patterns as a result of situational characteristics (in this case, news medium) are considered register variations (Biber & Conrad, 2009).

When using human coders, it is possible for a person to identify similarly framed communication across multiple media (e.g., Hamdy & Gomaa, 2012). However, when using computer-assisted techniques, a computer will not inherently know that certain language patterns occur more or less frequently in some media compared to others (Shane, 2019). As a result, computational tools may unintentionally focus on register variations when we want them to focus on frame variations. This is a phenomenon found in machine learning: for example, when training an algorithm on cancer tumors, a machine may identify images with rulers as more cancerous. This is because doctors take pictures of particularly large tumors with rulers. As a result, the machine learning algorithm is not actually identifying large cancers: it is identifying rulers (Patel, 2017).[33] To avoid this problem, it behooves scholars to make conscious efforts to account for register differences when studying framing across multiple media. This can be done by building individual algorithms or dictionaries for specific media.

News Register Variations. Though there are some similarities across all U.S. news media, the news is presented differently in print compared to broadcast television or radio.[34] It is therefore essential for scholars studying framing across multiple media to consider variations in news

[33] In this news story, Patel interviews Dr. Novoa, whose co-authored a *Nature* article uses neural nets to identify skin lesions. Dr. Novoa describes the ruler issue as a something that had occurred with a previous iteration of the algorithm ultimately used in the *Nature* piece.

[34] It is worth emphasizing the important role of the news production infrastructure. Even if there are only a few people on a news story byline, many more people in the newsroom review, critique, and revise news stories (whether it be written articles or broadcasted packages). Ethnographic work shows that internal guidelines greatly shape news production (Barkho, 2011).

subregisters. For example, when analyzing frames in print news and broadcast news media, it is essential to consider how the language form in written news is different from spoken news.[35]

In the United States, news stories generally adhere to the AP style's inverted pyramid structure, where the most important information is at the top (Park et al., 2012). The first sentence of a straight news story is called a lead (or "lede"). Within the news register, appositive noun phrases referring to people are common in news stories (Biber, 2002), such as: "Michael Bloomberg, former mayor of New York City." Because news stories report primarily on the past or ongoing actions of people, journalists rarely use inanimate objects in the subject position. In print, journalists also employ a variety of tenses to indicate the chronological order of events (Biber et al. 2002, p.156).

The greatest communicative difference between print news and broadcast news is that the former is written to be read, and the latter is scripted to be spoken. Though broadcast journalism writing does follow AP style, broadcast news segments are also structured using dramatic unity, which has three parts: climax (similar to a print lead), cause, and effect (Bradford, 2005). Another important difference is the quoting of speakers, guests, and experts. While print journalists can make selective choices about what to include from an interview, a news anchor has considerably less control over a guest who is on a news show (that being said, broadcast newsrooms can selectively choose video clips to air).

In terms of writing, broadcast journalism emphasizes conciseness, preferring short sentences over sentences with many clauses; its writing guides often recommend sentences with fewer than twenty words (e.g., Boyd, 2000). Subordinate clauses, adverbials, and passive voice are discouraged when writing in English for television or radio (Thompson, 2004). Another

[35] There are other news sub-registers that are not determined by media. For example, different news genres, such as tabloid and advocacy journalism, likely have register differences.

difference between broadcast news writing and print news writing is how quotes are attributed. In print news, attribution occurs after the quote, typically using a said inversion, but broadcast journalists declare the attribution before providing the quote (Boyd, 2000). Finally, broadcast news tends to be presented in the present tense, while tense is more variable in print news (Calle-Martin & Romero-Barranco, 2017).

Conclusion

In this chapter, I've presented a framework for studying framed language in news using natural language processing. The process for reducing language into numbers and operationalized into frames highlights requires the researcher to make many decisions when using computational methods to study framed language. Nevertheless, computational methods present new opportunities for political communication scholars to study framing. We can understand framed language better if we systematically analyze the structures of language, from the construction of words to the complex rules that guide their order. Framing scholars would also be especially adept at aligning linguistic patterns to social, cultural, psychological, or societal phenomena, given the substantial amount of work communication scholars have done on frame building and framing effects.

Chapter 4: Methods

There are three categories of variables in this analysis: economic variables, news variables, and public opinion variables. In this chapter, I outline my frame analysis and time series strategy to understand these groups of variables.

Data Collection

Economic Variables

This dissertation's analysis involves two economic variables: import penetration and the number of manufacturing jobs available in the United States. As the analysis will account for both temporal and geographic variation, it is necessary to have both import penetration and manufacturing job information available by month and by state.

Chinese Import Penetration. Import penetration refers to the proportion of domestic consumption that is fulfilled by Chinese imports (rather than domestic goods). Import penetration was calculated using the following formula:

Import Penetration = Imports from China / (Domestic GDP - Exports + Imports)

This long-known calculation has been used by economists (e.g., Autor, Dorn & Hanson, 2013) and by inter-governmental organizations (e.g., OECD, see Linder, 2007). For the national-level analysis, imports from China, overall exports, and overall imports were collected from the U.S. Census Bureau, which compiles monthly-level national data about imports and exports from as far back as 1985. The seasonally-adjusted monthly GDP for the United States was collected from the Federal Reserve Bank of St. Louis (n.d.), which compiles this information from the OECD.

For the 50 states, imports from China, overall exports, and overall imports were collected from the U.S. Census Bureau, which has compiled monthly-level state data about imports and exports since 2002. Country-specific data (i.e., state-level imports specifically from China) has been collected since 2008. The gross state product (GSP)[36] for each state in chained dollars is reported quarterly by the U.S. Bureau of Economic Analysis (to my knowledge, GSP by state is not calculated at the monthly-level).

Manufacturing employment. Monthly manufacturing employment data, both nationally and by state, were collected from the U.S. Bureau of Labor Statistics, which has been compiling industry-specific employment data since 1990. The Bureau of Labor Statistics (BLS) identifies the manufacturing sector using the North American Industry Classification System (NAICS); it includes 21 groups, including food manufacturing (NAICS 311), textiles (NAICS 313 and 314), paper manufacturing (NAICS 322), chemical manufacturing (NAICS 325), machinery manufacturing (NAICS 333), and transportation equipment (NAICS 336).[37]

News Text Data

The text data analyzed in this dissertation is comprised of three news corpora about U.S.-China trade: one corpus of national newspaper articles, one corpus of national television news transcriptions, and one corpus of local newspaper articles (for clarity, I will refer to "stories" to refer to both written and televised news content). All news stories were collected using LexisAdvance, an archive of local and national news media, using the Boolean search: China AND (United States OR U.S.) AND (trade OR tariff OR import OR export OR jobs). The news articles must have aired or been published between January 1, 2008 to December 31, 2018.

For the corpus of national newspapers, I collected articles from five nationally-read news organizations: *The New York Times* national edition,[38] the *Washington Post, Wall Street Journal*

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[36] GDP is to the country as GSP is to the state.

[37] For a full list of industries, please visit the U.S. BLS website: https://www.bls.gov/iag/tgs/iag31-33.htm

[38] This differs from their local edition, which focuses on news within New York state, see https://www.nytimes.com/1997/01/22/business/times-expanding-nationwide-distribution.html

and *Foreign Affairs*. The first three publications began as print publications and are considered newspapers of record (Golan & Lukito, 2015; Ridout, Fowler, & Searles, 2012). *Foreign Affairs* is a more specialized print magazine, it is considered a uniquely influential publication for people interested in foreign policy (e.g., trade). Though the print version of *Foreign Affairs* is published every other month, the website publishes their print stories online weekly. LexisAdvance collects both the printed articles and online articles published by all four outlets.

For the corpus of national television, I collected news program transcripts from five national broadcast outlets: ABC, CBS, CNN, Fox, and NBC. ABC, CBS, and NBC are considered the "big three" networks (Baum, 2013). CNN, founded in 1980, was the first network to provide 24-hour news coverage, fundamentally changing the news cycle (Rosenberg & Feldman, 2008); CNN's use of graphic and salacious content is particularly notable in foreign news reporting (Robinson, 2005). Fox was founded in 1996 by Rupert Murdoch to be a conservative alternative and competitor to CNN. Early studies have highlighted the importance of Fox news to Republicans' political attitudes and action (DellaVigna & Kaplin, 2007).

For the corpus of state-wide newspapers, I modified the Boolean search used to collect newspaper articles by adding the state's name to the search: China AND (United States OR U.S. OR [STATE]) AND (trade OR tariff OR import OR export OR jobs).[39] LexisAdvance maintains an archive of publications by state.[40] The search produced results from 438 sources, across the 50 states (*The New York Times* national and regional editions and the *Washington Post* were excluded from this corpus). For a full list of the local outlets, please see Appendix A.

[39] For example, the search for Wisconsin would be: China AND (United States OR U.S. OR Wisconsin) AND (trade OR tariff OR import OR export OR jobs)

[40] In the original LexisNexis Academic, which is defunct as of 2020, this would include the "newspapers", "major newspapers", and "small town papers" sources.

There were 5,999 transcripts from national broadcasts, 82,404 articles from national newspapers, and 125,606 articles from local newspapers.

Public Opinion Variables

For this dissertation, I was interested in three public opinion variables: public perceptions of jobs in the local area, public opinion of how the President is handling the economy, and public opinion of how the President is handling his job (sometimes known as "Presidential job approval"). To construct time series of these public opinion variables, I collected and aggregated data from surveys by ABC (conducted by TNS Intersearch), CBS (conducted by Social Science Research Solutions), NBC (conducted by Hart Research Associates/Public Opinion Strategies), Gallup, Pew Research Center (conducted by the Princeton Survey Research Associates International) and CNN (conducted by Opinion Research Corporation) from January 1, 2008 to December 31, 2018; this was done through the Roper iPoll archive, a popular database repository for public opinion surveys (Robison, 2015).[41] Studies interested in aggregated public opinion have pooled studies similarly across time (e.g., Burden & Mughen, 2003). For a survey to be included, it must have: (1) at least one question about local job availability, perceptions of how the President was handling the economy, or Presidential job approval; (2) information about the participants' state of residence; *and* (3) information about the participants' political party. In order to conduct a national-level and state-level analysis, I constructed 102 time series for each public opinion variable: 51 for Democrats' public opinion and 51 for Republicans' public opinion (1 time series for each state, and 1 national time series).

[41] Although I also considered surveys from Fox, Associated Press, and Bloomberg, they did not ask the three relevant questions with enough frequently within the study's time frame.

Perception of Jobs Available in the Local Area. For this variable, I collected surveys asking one of the following questions (parentheses indicate words that did not appear in all the questions):

(1) Thinking (now) about jobs where you live, would you say there are plenty of jobs available or are jobs difficult to find?

(2) Thinking (now) about jobs in your local area/community, would you say there are plenty of jobs available or are jobs difficult to find?

(3) "Would you say there are plenty of jobs available in your local area or are jobs difficult to find?

Participants had four response options: Plenty of jobs available (3), lots of (some) jobs/few (of) others (2), jobs are difficult to find (1), or don't know/no answer (99). There were 43 surveys that fulfilled the aforementioned conditions from 2008 and 2018, each survey had roughly 1000 participants. I then took the average of the question for Democrats and Republicans, for each state and nationally, producing 102 irregular time series (51 for Democrats, and 51 for Republicans, by state and nationally). Using these irregular time series, I constructed 102 latent continuous time series variables at the monthly-level to cover the full time span (Stimson, 2018).

Public Opinion of how the President is Handling the Economy. For this variable, I collected surveys asking one of the following questions:

(1) Do you approve or disapprove of the job [PRESIDENT][42] is doing on the following issues? The economy?

[42] In the survey, [PRESIDENT] refers to George [W.] Bush, Barack Obama, or Donald Trump. None of the survey questions used the title "President" explicitly.

(2) Do you approve or disapprove of the job [PRESIDENT] is doing in handling the economy?

(3) Do you approve or disapprove of the job [PRESIDENT] is doing… with the economy?

For most of the surveys, participants had three possible responses: approve (1), disapprove (0), or don't know/no answer (99). A handful of surveys asked this question with a 6-point scale (strongly approve, approve, slightly approve, slightly disapprove, disapprove, and strongly disapprove); these were aggregated into approve and disapprove to align with the majority of the questions. There were 135 surveys that fulfilled the aforementioned conditions from 2008 to 2018. All of these surveys also asked a Presidential job approval question (see below for the construction of that variable).

To construct monthly time series variables, I took the average response for each question by state and party (Democrats and Republicans). I then took the average of surveys occurring in the same month. This produced 102 time series (51 for Democrats, and 51 for Republicans, by each state and nationally). As there was at least 1 survey per month with this question, it was not necessary to produce a latent variable.

Public Opinion of Presidential Job Approval. For this variable, I collected surveys asking one of the following questions:

(1) (In general,) do you approve or disapprove of the way [PRESIDENT] is handling his job as president?

(2) Do you approve or disapprove of the job being done by [PRESIDENT] as president?

Participants were given the option to answer approve (1), disapprove (0), or don't know/no answer (99). There were 153 surveys that fulfilled the aforementioned conditions from 2008 to 2018 (most surveys also asked participants about whether they approved or disapproved of how the President was handling the economy). Following the same procedure used to process the other public opinion variables, I took the average response for each question, by state and party. I then averaged surveys occurring in the same month. This produced 102 time series (51 for Democrats and 51 for Republicans, by each state and nationally). As there was at least 1 survey per month with this question, it was not necessary to produce a latent variable.

News Frame Analysis

To construct the news frame variables, I performed a computer-assisted content analysis to understand how news media framed U.S.-China trade and its impact on the U.S. economy. I define a news frame as a collection of framing devices (overt language patterns) used to make sense of or help explain a news story. This frame analysis takes a two-step approach: in the exploratory phase, I analyze the three corpora using qualitative and computational techniques. The goal of this phase is to build a lexico-syntactic dictionary that operationalizes framed content. This is unique relative to other dictionary strategies in that it considers both lexicon and syntax. Lexico-syntactic dictionaries have been used to extract event information (Hung, Lin & Hong, 2010), identify antonyms (Lobanova, Van der Kleij, & Spenader, 2010), and perform sentiment analysis (Schouten, et al., 2016). In the deductive phase, I manually validate the lexico-syntactic dictionaries and apply them to the corpora to understand how U.S.-China trade is framed in local newspapers, national newspapers, and national broadcast television news.

Exploratory Phase

In this phase, I reviewed excerpts and full articles about U.S.-China trade to identify frames and construct lexico-syntactic dictionaries. I began by analyzing the top words and bigrams in the three corpora; this strategy has been employed in recent text analysis research

(Muddiman, McGregor & Stroud, 2019). I also constructed several structural topic models; for results, see Appendix F.

Text Processing

LexisAdvance provides articles in a .txt or .docx format. In order to perform natural language processing tasks like dependency parsing or tokenizing, it is necessary to clean the text data. One advantage of using LexisAdvance is the consistency of the formatting: all stories begin with meta-data information and ends with copyrighted information. It was therefore possible to tokenize a file into individual articles (for print) or programs (for broadcast). Once each article was separated as a different entry (row) in a dataset, I stored the meta-data presented at the top of each article (e.g., date, headline, outlet, byline) as separate variables and removed the header and footer of each article (e.g., solicitations to follow a journalists' account). It is worth noting that this process is not perfect, as news organizations occasionally vary how they demarcate header and footer information.

As I was interested in frame devices at the statement and argument level, the pre-processing steps I took were largely additive—rather than reducing data layers by stemming or using a bag-of-words technique, I annotated the corpora with additional syntactic information. First, I annotated pronouns with their appropriate co-reference using a technique called co-reference resolution. This process is available through the coreNLP wrapper in the cleanNLP R package (Arnold, 2017). While time consuming, this process is very useful for making sense of sentences once tokenized. I then subjected the corpora to a dependency parser and part-of-speech tagger using the R package spacyR, which is a wrapper for the Python library spaCy (Benoit, 2018). In addition to being a state-of-the-art dependency and POS tagger, spaCy is also one of the fastest annotators available (Choi Tetreault, & Stent, 2015). This tagging process tokenizes words and annotates each word for their: part-of-speech, dependency relationships, and lemma (lemmatizing allows you to search for lemmas without losing the already-annotated part-of-speech information).

To identify meaningful cue, statement, and argument framing devices, my unit of analysis was a news excerpt. For the written news content (national and local), I tokenized each article into three-sentence-tokens. For the spoken news content (national only), I tokenized each program by a speaker's remarks. Thus, a news excerpt for print news constituted three sentences and a news excerpt for broadcast news constituted a speakers' remarks. I then isolated excerpts that contains at least one word from all three categories:

1) China OR Xi OR Hu OR Chinese OR CCP[43]
2) United States OR U.S. OR U.S.A. OR USA OR US OR america (without "south" or "central" before) OR Trump OR Obama OR Bush OR Republican OR GOP OR Democrat OR Alabama OR Alaska OR Arizona OR Arkansas OR California OR Colorado OR Connecticut OR Delaware OR Florida OR Georgia OR Hawaii OR Idaho OR Illinois OR Indiana OR Iowa OR Kansas OR Kentucky OR Louisiana OR Maine OR Maryland OR Massachusetts OR Michigan OR Minnesota OR Mississippi OR Missouri OR Montana OR Nebraska OR Nevada OR New Hampshire OR New Jersey OR New Mexico OR New York OR North Carolina OR North Dakota OR Ohio OR Oklahoma Oregon OR Pennsylvania OR Rhode Island OR South Carolina OR South Dakota OR Tennessee OR Texas OR Utah OR Vermont OR Virginia OR Washington OR West Virginia OR Wisconsin OR Wyoming
3) trade OR tariff OR import OR export OR job

Qualitative Analysis

I reviewed these excerpts in 500-excerpt samples (250 written news, three-sentence excerpts and 250 spoken news, speaker's statement excerpts). For each excerpt, I coded the argument of the excerpt, including the sentiment levied at China, the United State, politicians, other stakeholders, the economy, and trade policy; references to free trade theory, free market

[43] Another acronym for the Chinese Communist Party is CPC, but this is not used in AP Style.

theory, protectionism, or another economic theory; and the nouns and verbs used, including the grammatical tense. Though there is obviously some natural discourse variety, these arguments are also grounded in long-held attitudes regarding trade and the United States' relationship with China and therefore have notable patterns across multiple stories.

For example, consider the first three sentences from an article published by *Nogales International*, an Arizona newspaper owned by Wick Communications (sentences are numbered):

> America's soy growers are lined up even more precisely in the crosshairs of President Trump's contentious tariff confrontation with China. [1] President Trump announced Monday that $200 billion in additional Chinese goods will be hit with a 10 percent tariff, deepening the likely free fall in prices that producers of soy and soy products are feeling directly in their wallets and which threaten the stability of their market long-term. [2] "Soybean prices are declining as a direct result of this trade feud," said John Heisdorffer, Iowa soybean grower and president of American Soybean Association (ASA). [3]

In this excerpt, tariffs (a protectionist policy) are portrayed negatively because the resulting trade war negatively impacted the sale of U.S. soybeans. The second and third sentence contextualize the lead sentence, which begins by focusing on the soy growers (as opposed to the tariffs). Phrases such as "in the crosshairs" reinforce the war metaphors commonly used in "trade war" reporting. The focus of all three sentences is on the victim: soybean farmers. Even in the second sentence, the subject, "President Trump," in the first clause is in service to emphasizing the consequences for the farmers, mentioned in the dependent clause. And importantly, the last sentence (the quote) attributes the decline in soybean prices to the trade war (i.e., when countries recursively impose tariffs on one another's products), creating a clear structure: soybean prices(nsubj) are declining(ROOT) as [a result [of the trade(nn|compound) feud(pobj)]]. The person himself is a soybean grower, as noted in the attribution. Therefore, this excerpt frames tariffs, a protectionist policy, as bad because it will harm farmers hoping to sell soybeans (i.e., agricultural exporters).

After 1000 randomly sampled excerpts (two samples of 500), I reached a saturation point such that I could not derive any new framing devices.[44] Categorizing the framing devices resulted in 11 frames, 10 of which will be discussed in this dissertation: (1) trade benefits businesses, (2) protectionism harms the economy, (3) protectionism makes things cost more, (4) free trade leads to job loss, (5) protectionist policies will bring jobs back, (6) the U.S. is too dependent on Chinese imports, (7) China engages in intellectual property theft, (8) China is a currency manipulator, (9) China has unfair trade restrictions, and (10) Chinese products are of poor quality (for more information about the frames, see Chapter 5).[45] (These frames will be described in more detail in Chapter 5.) Given that the data were analyzed in excerpts of three sentences or a speaker's statement, the frames identified had notable language features at the cue, statement, and argument frame level (McLeod & Shah, 2015). These language patterns, identified through the coding process, serve as the foundation of the lexico-syntactic dictionaries for both print and broadcast news media.

Lexico-Syntactic Dictionary Construction

A lexico-syntactic dictionary is a dictionary containing lexicon and syntactic features of that lexicon (typically, part-of-speech or dependency relationships). The simplest lexico-syntactic dictionary would be a part-of-speech tagged dictionary of keywords. The lexico-

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[44] The concept of "theoretical saturation" is popular in grounded theory methodology, but its meaning is disputed. Though I would not describe my qualitative analysis as grounded theory, the cyclical process of my coding procedure is grounded theory-inspired: I "open coded" various language features, thematically categorized them in a process not unlike axial coding and wrote memos between iterative coding stages.

[45] The eleventh frame, "trade is important for diplomacy" will not be considered because it appeared less frequently compared to the other frames and because diplomacy itself does not have a direct consequence on people's domestic economic circumstances.

syntactic dictionaries constructed for this dissertation to study different frames contain a combination of n-grams or keywords (cue frame), within-sentence lexico-syntactic combinations (statement frames), and multi-sentence lexico-syntactic combinations (argument frames). A sample of the “protectionist policies protect jobs” dictionary can be found in Table 3 (for illustrative purposes, I only show dictionary entries for the first three words).

Table 3: Sample Lexico-Syntactic Dictionary

#	W1_l[1]	W1_dep[2]	W1_pos[3]	W2_l	W2_dep	W2_pos	W3_l	W3_dep	W3_pos	Sen
1	union	nsubj	NN	advocate	ROOT	VB	tariff	obj	NN	T
2	union	nsubj	NN	demand	ROOT	VB	tariff	obj	NN	T
3	union	nsubj	NN	support	ROOT	VB	tariff	obj	NN	T
4	support	ROOT	VB	by	prep	ADP	union	obj	NN	T
5	tariff	nsubj	NN	bring	ROOT	VB	job	obj	NN	T
6	tariff	nsubj	NN	bring	advcl	VB	job	obj	NN	T
7	bring	ROOT	VB	back	advmod	ADV	job	obj	NN	T
8	bring	advcl	VB	back	advmod	ADV	job	obj	NN	T
9	protect	ROOT		American	amod	JJ	job	obj	NN	T
10	save	ROOT		U.S.	amod	JJ	job	obj	NN	T
11	jobs back									F
12	tariff	nsubj	NN	protect	ROOT	VB	job	obj	NN	T
13	union	nsubj	NN	said	ROOT	VB	bring	ROOT	VB	F
14	union	nsubj	NN	said	ROOT	VB	bring	ccomp	VB	T

[1] lemma
[2] dependency annotation, from Universal Dependencies
[3] part-of-speech annotation, from Penn Treebank

In Table 3, each entry of the dictionary contains: keywords of interest (often three, particularly in the subject-verb-object construction, though there could be more), their part of speech, and the expected dependency in sentence (dependencies provide more information than part-of-speech, such as telling you whether a noun is in the subject or object position of a phrase). This dictionary includes cue frames, statement frames, and argument frames. Cue frame entries only have one entry (e.g., row 9), and this entry may have more than one word. Statement frames include both dependency and part-of-speech information. The "sen" column can be used to identify sentence-level frame devices (i.e., statement frames) as sentence frames are labeled "T" (true), while cue and argument frames are marked "F" (false). Finally, argument frames have part-of-speech information and dependency information. The longest entries tended to be argument frames, as they can encompass multiple sentences.

In addition to these dictionaries, I also excluded sentences with negations (e.g., "tariffs do not protect jobs") using the "neg" dependency tag, which identifies the word related to the English negation word "not." To account for negations in the next sentence, I excluded all sentences for which the subsequent sentence began with "However" or "But."

Because written news varies greatly in structure compared to spoken news (this is notable even in the data cleaning process), two separate dictionaries were constructed for each frame, one for broadcast television and one for print news. The broadcast register included parts-of-speech categories that are not common to written news, such as modals and superlatives.

Deductive Phase

To validate my dictionaries, I manually coded a third random sample of 500 news excerpts (250 from print news and 250 from broadcast transcripts) for the presence of each frame (an excerpt could contain more than one frame). I then subjected these excerpts to the dictionaries. Finally, I ran an intercoder reliability test between myself and the labels derived from the dictionary method. The process of comparing dictionary-derived labels to human coding has become fairly common in mass communication (e.g., Muddiman, McGregor, &

Stroud, 2019; Guo et al., 2016) and is an essential for validating the quality of computational tools (Bousman & Trilling, 2016). Table 4 displays the intercoder-reliability scores using Krippendorff's Alpha (2011).

Table 4: Intercoder Reliability Between the Dictionary and me for 10 U.S.-China Frames

Frame	**ICR Print / ICR Broadcast**
1. Trade benefits businesses/industry	0.79 / 0.75
2. Protectionism harms the economy	0.81 / 0.77
3. Protectionism makes things cost more	0.92 / 0.80
4. Free trade leads to job loss	0.88 / 0.76
5. Protectionist policies will bring jobs back	0.73 / 0.80
6. The U.S. is too dependent on Chinese imports	0.80 / 0.72
7. China engages in intellectual property theft	0.94 / 0.90
8. China is a currency manipulator	0.98 / 0.89
9. China has unfair trade restrictions	0.79 / 0.81
10. Chinese products are of poor quality	0.83 / 0.88

Once these frames had been verified, I applied the dictionary to all the sentence excerpts. I then counted the use of the frame devices in the excerpts at the story-level (one segment, and certainly one story, could contain more than one frame).

Time Series Aggregation

My dissertation will end with several time series analyses, including variables for Democrats' and Republicans' opinions about the President and the economy, news frames in broadcast television and print news media, and national and state-level economic information related to the China trade shock. Time series is a popular longitudinal, quantitative analysis used to study temporally lagged relationships between variables (Wells et al., 2019). The most commonly used multivariate time series model used is the Vector Auto-Regression model, known as the VAR model. For this dissertation, I used a VAR model to analyze the national-level variables. In a VAR model, every variable included is modeled as an equation of its own lagged values, the lagged value of other variables in the model, and an error term (Box-Steffensmeier, Freeman & Pevehouse, 2014).

In addition to the national VAR model, I also constructed a fixed-effect multi-level VAR model—the mlVAR model—to study state-level variations using the VAR structure. One advantage of the mlVAR is the ability to construct state-level formulas. However, the mlVAR has several disadvantages; most importantly, one cannot construct Granger causality tests and impulse response functions on top of a mlVAR (both are important techniques for interpreting VAR results). To supplement these results, I illustrate my findings with three state cases.

Chapter 5: Frame Analysis

The collections of U.S. news stories mentioning U.S.-China trade from 2008 to 2018 consisted of three corpora: articles from five national print news organizations: Foreign Affairs, *The New York Times*, *Washington Post*, *Wall Street Journal* and (n = 82,404); shows from five national broadcast television: ABC, CBS, CNN, Fox, and NBC (n = 5,999); and articles from 459 local newspapers across all 50 states (n = 125,606). Following the processing procedure described in Chapter 4, I analyzed 129,238 excerpts from these corpora: 125,889 three-sentence written news snippets (69,688 from local news media and 56,201 from national news media) and 3,349 five-sentence spoken news snippets.

In this chapter, I describe the 10 frames identified in U.S. news coverage about U.S.-China trade. These can be aggregated into three broad story frames: pro-trade frames, anti-trade frames, and anti-China frame. In the articles without relevant excerpts, China was referenced tangentially (e.g., NAFTA trade discussions) or trade was tangential to other topics, such as military relations with China. A small percentage of the television content focused on cap and trade (this was removed from the corpus). Table 5 displays the number of news excerpts using each story frame (keep in mind that an excerpt could have more than one frame).

Table 5: Frequency of Story Frames in News Excerpts about U.S.-China Trade, 2008-2018

	National Broadcast	**National Print**	**Local Print**
# of articles	5,999	82,404	125,606
# of excerpts	3,349	56,201	69,688
Articles with excerpts	3,221	42,893	65,847
Frame Use (# Articles)			
1. Pro-Trade	1,439	13,480	27,557
2. Anti-Trade	549	8,184	16,331
3. Anti-China	1,656	14,059	33,261

The anti-China story frame was the most common in both national newspaper and television, followed by the pro-trade story frame. The anti-trade frame was the least common.

Frame Variations by Broadcast and Print News Subregisters

Though broadcast and print national news organizations used all 3 frame stories, the way in which these frames manifested varied greatly. For this reason, the processing and dictionary applied to the broadcast text was different compared to the analysis of print text. For print media, I analyzed three-sentence segments if at least one segment appeared in the first seven sentences of a news story. As broadcast news uses shorter sentences and includes a greater number of back-and-forth interviews, I analyze a speaker’s remarks.

Much of this variation is attributable to the situational characteristics of broadcast versus print news production. Most importantly, broadcast uses spoken language and print uses written language. Correspondingly, broadcast sentences tend to be shorter and more considerate of prosody (Cotter, 1993). In terms of production, though broadcast news is scripted, and interviews are planned, broadcast newsrooms do not know with absolute certainty what a guest or interviewee will say. By contrast, print news content undergo substantial revisions by multiple authors—no written word is typically published without copy editing from multiple individuals (journalists, reporters, and editors). The spontaneity of broadcast journalism may make it easier for individuals (journalists and guests) to make casual evaluative remarks and to advocate for or against specific economic policies.

As a result, “spoken,” broadcast U.S. news also uses more linguistic markers typically associated with subjective, or “opinionated” language (Graber & Holyk, 2011). For example, modals (e.g., should, must, could) matter more to broadcast news writing (Montgomery, 2007). One excerpt from a CNN news story included the following pro-trade quote: “America should think about free trade, global economy as something we want to embrace" (CNN, 2011). Adverbials and superlatives also occur more frequently in broadcast news compared to written news (Bliss & Hoyt, 1994; Lombardo, 2009). This is especially true for interviews in broadcast television (Haddington, 2004).[46] A related concept is "stance language," referring to language markers that are used to express an opinion or issue position. Table 6 displays the frequency of the two markers indicating stance in the national television and print news corpora: modal verbs and superlative adjectives.

Table 6: Frequency of Stance Markers in National Print and Broadcast (TV) News

	TV (# of articles)	TV (%)	NP (# of articles)	NP (%)
Modals	850	26.39%	3,225	0.04%
Subjective Adj.	641	19.90%	5,931	0.09%

How Much Local News is National?

The first research question asks whether local news media coverage will focus on national, rather than local, stories. For this part of the analysis, the unit of analysis will be full articles, but only those with relevant excerpts. To test this, I constructed two dictionaries, one with national words and one with state-level words. The national dictionary included the words "President, Trump, Obama, Bush, America, United States, Washington DC". In the state dictionary, for each state, I included: the governors within the time frame, the name of the state, the top six largest cities, the capital (if not already listed), and the names of all the counties. For example, the Wisconsin entries in the dictionary included the following words:

[46] It's worth acknowledging that subjective language use is not inherently a violation of the standard of objectivity in U.S. journalism. As Wahl-Jorgensen (2012) notes, binarizing subjectivity and objectivity in journalism obscures the need for subjective language in emotional narratives.

> Wisconsin, Doyle, Walker, Evers, Milwaukee, Madison, Green Bay, Kenosha, Racine, Adams, Ashland, Barron, Bayfield, Brown, Buffalo, Burnett, Calumet, Chippewa, Clark, Columbia, Crawford, Dane, Dodge, Door, Douglas, Dunn, Eau Claire, Florence, Fond du Lac, Forest, Grant, Green, Green Lake, Iowa, Iron, Jackson, Jefferson, Juneau, Kenosha, Kewaunee, La Crosse, Lafayette, Langlade, Lincoln, Manitowoc, Marathon, Marinette, Marquette, Menominee, Monroe, Oconto, Oneida, Outagamie, Ozaukee, Pepin, Pierce, Polk, Portage, Price, Racine, Richland, Rock, Rusk, St. Croix, Sauk, Sawyer, Shawano, Sheboygan, Taylor, Trempealeau, Vernon, Vilas, Walworth, Washburn, Washington, Waukesha, Waupaca, Waushara, Winnebago, Wood

Table 7 displays the frequency and percentage of articles in the local newspaper dataset.

Table 7: Frequency of References to the State or Nation in Local Newspaper Articles

	# of Articles	**% of Corpus**
Stories mentioning state words	17,780	27.00%
Stories mentioning state & national words	16,201	24.60%
Stories mentioning national words	31,866	48.39%

These results suggest that nearly half of the local news articles were actually stories about national news (48.4%). A little more than a quarter of the corpus used state terms only (27.0%), and the remaining articles (24.6%) used a combination of both. In addition to this, byline meta-data suggested that 10,452 of the articles, 15.8% of the corpus, were from AP news wires (using the byline “AP” or “Associated Press”). These trends show that a substantial portion of the state-level news media focused on national stories, rather than local stories (RQ1).

Frames

In the following section, I describe the frames. A list of the frames and cue, argument, and statement frame device constructions can be found in Table 8.

Table 8: Description of U.S.-China Trade News Story Frames

	Name/Description	U.S. Market Focus	Cue Frame Device	Statement Frame Device	Argument Frame Device
Pro-Trade	Trade benefits businesses.	Exports		China[n] + partner[v/n] + U.S.[n] China[n] + help[v] + U.S.[n] U.S.[n] + helped[v] by + China[n] U.S.[n] + attract[v] + China[n]	Quoting free trade economists; anecdotes about state/city-specific deals and visits
	Protectionism harms businesses.	Exports/Imports		Business[n] + fear[v] + tariff [n] Tariff[n] + feared by[v] + business[n] U.S. econ[n] + slowdown[n] + tariff[n] Tariff[n]+ slowdown[n] + U.S. econ[n] Effect of tariff[np] + harm[v] Effect of tariff[np] + harmful[adj] Victim[n] + trade war[n] Stock market[np] + fall[v] + trade war [np] Trade war[n] + stock market[np] + fall[v]	Anecdote (about specific business) or statistic to illustrate broader pattern
	Protectionism increases good's prices.	Imports		Tariffs[n] + raise[v] + prices[n] Prices[n] + raised by[v] + tariffs[n] <good>[n] + cost more[v] + tariffs[n] <good>[n] + expensive[adj] + tariff[n] Tariffs[n] + increase cost[n] + good[n]	Anecdote (of specific business) or statistic to illustrate broader pattern.
Anti-Trade	Free trade leads to job loss.	Labor	Chinese free trade zone; China shock; trade shock	China trade[np] + job loss[np] Job loss[np] + China trade[np] Globalization[n] + job loss[np] Job loss[np] + globalization[np]	Reference to unions as a stakeholder
	Protectionist policies protect jobs.	Labor	jobs back	Union[n] + promote[v] + tariff[n] Tariffs[n] + bring[v] + jobs[n] Tariffs[n] + protect[v] + business[n]	Reference to unions as a stakeholder
	U.S. demand is too import-dependent.	Imports	Walmart	"made in china" + cheap [adj]	Discussion of low cost of goods; anecdotes about big box stores
Anti-China	China steals U.S. intellectual property.		Intellectual property theft; corporate espionage	China[n] + steals[v] + U.S.[n] U.S.[n] + stolen by[v] + China[n]	
	China is a currency manipulator.	(Imports)	Currency manipulat	China[n] + manipulates[v] + yuan[n] China[n] + peg[v] + yuan[n] + (to) dollar[n]	
	China has unfair trade restrictions.	(Exports)	Chinese protectionism; indigenous innovation	China's restriction[np] + unfair [adj] China[n] + violates[v] + law/trade norms[np] China[n] + restricts[v] + imports[n] China[n] + unfair[v] + exports[n] China[n] + uses[v] + non-tariff barriers[np] China[n] + protectionist[adj]	Reference to IGOs (e.g., U.S. grievance to WTO); arguments include U.S. and Chinese perspectives
	Chinese products are of low quality.	Imports		Chinese import + contaminated [adj] "made in china" + low quality[adj]	Reference to food products or goods with lead; Quotes from U.S.FDA.

Pro-Trade Story Frames

In the first story frame, ***<u>pro-trade story frames</u>***, there are three argument/statement frames that advocate for free trade policies or critique protectionist policies. These frames promote free trade theory and criticize any trade barriers, including and especially tariffs. The first is <u>trade</u> **benefits business**. This includes anecdotal stories about U.S. businesses selling goods to Chinese markets or about increasing U.S. exports. For example, *Boston Globe* published an Associated Press article with the following anecdote about equipment company Caterpillar Inc. (based in Illinois): “Further gains in exports should bolster manufacturers, who struggled during the recession. Heavy equipment maker Caterpillar Inc., for instance, has predicted that its sales will increase next year, reflecting in part greater demand from China and other Asian markets” (Associated Press, 2009). In this excerpt, a heavy equipment maker’s (heavy equipment is a manufacturing sector) “sales will increase” because of Chinese demand, signaling benefit.

The second frame is that **protectionism harms businesses**. This is a supply-side focused frame that argues against the use of policies that limit open trade between countries, including quotas and tariffs. These stories focus on U.S. businesses suffering from the cost of raw goods or are struggling because foreign markets are no longer buying goods due to protectionist policies (e.g., soybeans). The rising cost of goods for U.S. manufacturers was a key criticism of President Trump’s tariffs in 2018, as seen in this article from Gannett-owned Maryland newspaper *Daily Times*: “While the direct impact on consumer goods appears to be limited for now, Trump's 25 percent tariffs on Chinese goods will hit products sold to certain U.S. manufacturers, medical device makers and farmers, among others” (Bomey, 2018; this piece also ran in *USA Today*). “Hit” was a fairly common verb used generally in discussions about the increased cost of goods, but the key here is that the cost will be paid for by manufacturers and makers, not just consumers.

A related group of news stories also focused on stock market responses to tariffs, such as in the lead of this Associated Press piece published by West Virginia newspaper *The Herald-Dispatch* about the Dow Jones Stock Exchange: “Car makers and technology and industrial companies fell Thursday as investors focused on the U.S.-China trade dispute, which could reduce company spending and earnings” (Associated Press, 2018). These articles attributed stock market drops to ongoing trade disputes between the United States and China.

The third frame is **protectionism makes goods cost more**. This frame emphasizes the demand-side (i.e., the cost of goods) and focuses on the cost of final goods, like iPhones, on U.S. consumers. The focus on final products distinguishes it from the second frame (protectionism harms businesses), as the latter is focused on raw goods used by U.S. companies, generally to produce final goods. For example, one article in a Gannett-owned New Jersey newspaper (*Ashbury Park Press*) about tariffs imposed by President Trump included the following sentences:

> Items ranging from address books to air conditioners, bicycles to baseball gloves, food to furniture have been added to the list of products made in China that will face additional charges when they arrive in America. Retailers say American consumers will pay the price for the new trade policy. (Verdon, 2018)

Because of the size of President Trump’s tariffs—and the high demand for Chinese goods in the United States—this was an especially common frame during the Trump administration (2016-2018). By contrast, President Obama’s tariffs focused specifically on tires.

Anti-Trade Story Frames

In the second story frame, ***<u>anti-trade story frames</u>***, there are three argument/statement frames that advocate for protectionist policies or putting limits on free trade. These frames emphasize the so-called “losers” of free trade (i.e., workers in import-competitive sectors) and encourage the use of protectionist policies, especially tariffs, to protect these industries. The first frame, **free trade leads to [manufacturing] job loss** broadly included stories and statistics emphasizing job loss as a result of the trade imbalance between China and the United States. One vein of this frame was more China-specific, focusing specifically on the China Shock. Other articles discussed globalization and its harm on specific U.S. industries more broadly, using China as a key example. Articles using this frame frequently referenced statistics related to manufacturing job loss, such as in this article published in North Carolina newspapers *Raleigh News & Observer* (the original publisher), *The Charlotte Observer* and *Winston-Salem Journal*: “About 75 percent of North Carolina's displaced jobs, or 59,867, were in manufacturing […] ‘Trade gaps with China have exacted a heavy toll from working North Carolinians in the form of lost jobs, wages and opportunities,’ said John Quinterno” (Murawski, 2008). Manufacturing employment and wages were frequently discussed in this frame; other industries (including manufacturing-reliant industries, like agriculture) were not.

The second statement/argument frame, **protectionist policies protect jobs**, focused on protectionist policies as a solution to preventing manufacturing job loss in the United States. Sometimes, these frames highlighted the role of unions advocating for protectionist policies, particularly during the Obama administration, as seen in this AP news wire published by the Oklahoman : “The United Steelworkers Union pushed for penalty tariffs, blaming the loss of 5,000 U.S. tire workers’ jobs since 2004 on U.S. tire imports from China more than tripling from 2004 to 2008” (Associated Press, 2011). Obvious, this quote also exhibits the <u>free trade leads to job loss</u> argument/statement frame, by bringing up “the loss of 5,000 Y.S. tire workers’ jobs.”

The use of multiple frames aligns with Entman's (2003) functions of a frame: the problem this excerpt identifies is the jobs lost as a result of Chinese imports, and the solution includes tariffs.

One occasional misconception in this frame, particularly in the latter years (2016-2018) is that tariffs would "bring jobs back" to the United States. This argument was mentioned in a handful of local articles, such as in the following *Pittsburgh Post Gazette* story: "Trump's new tariffs will continue to strengthen Pennsylvania's local steel and aluminum producers, bring jobs to the state and solidify America's path toward renewed economic strength" (Urban, 2018). In national news media (newspapers and television), journalists typically refuted the argument. A related, but more common, argument in this frame was that tariffs would encourage local industries to purchase raw goods from American companies—in the above excerpt, Urban implies this argument by saying that tariffs will benefits "Pennsylvania's local steel and aluminum producers."

The third statement/argument frame was that **the U.S. is too dependent on Chinese goods**. Unlike the previous frames, this argument focused on U.S. demand for exports from China rather than job loss. Articles using this frame contended that U.S. consumers have gotten used to the significantly low cost of Chinese imported goods, as seen in the following CNN excerpt: "We can't blame China for us spending too much money and printing too much money and buying cheap goods and doing so much to undermine our corporations here and our industries" (Sen. Ron Paul [R] as quoted in CNN Newsroom, 2011).

Anti-China Story Frames

The third story frame**, *anti-China story frames***, does not focus on economic mechanisms like the previous story frames did. Instead, these articles frame China as a uniquely unfair actor that violates trade norms. There are four argument/statement frames in this category. Unlike the previous story frames, these are less cohesive as a narrative, but point to the various ways in which people believe China is an unethical trading partner. In this frame, protectionist policies are a means to an end—they do not necessarily protect American jobs so much as they would punish China for unfair economic practices. This is an essential distinction between this story frame and the anti-trade story frame, which portray protectionist policies as beneficial the U.S. economy, rather than punitive to China.

The first statement/argument frame in this category focuses on **China's intellectual property theft** and criticizes Chinese companies for stealing trade secrets or intellectual property (other terms for this include: IP theft, and corporate, economic, or cyber espionage). Though these articles typically framed the impact in terms of national effects and consequences, there were several local stories related to cyber theft, such as one Pennsylvania-specific story written by local newspaper *Tribune-Review* (the story's main focus was on a visit by the Chinese Vice Premiere to Pittsburg): "A federal grand jury based in Pittsburgh last year indicted five members of the People's Liberation Army "China's military" on charges of participating in government-sponsored computer espionage, including stealing trade secrets from companies such as Alcoa, U.S. Steel Corp. and Westinghouse Electric Co." (Fontaine, 2015).

The second focused on **China as a currency manipulator**. The core logic of this frame is that the Chinese government artificially keeps their currency low to make their exports cheaper (and therefore more desirable) to consumers globally, particularly in the United States. Whether this claim is accurate depends largely on the time frame one considers (Staiger & Sykes, 2010). In 2012, when Republican Presidential candidate and Governor Mitt Romney claimed China was a currency manipulator, some economists argued that China's currency manipulation in the early 2000's was "a major cause of the trade deficit" (Scott, 2014) and contributed to the size of the

China shock (Bergsten & Gagnon, 2017).[47] But by 2016, these economists remarked that China was no longer engaging in currency manipulation (e.g., Bergsten, 2016). Despite this, politicians—particularly President Donald Trump—continue to claim that China is a currency manipulator. In 2019, the Treasury Department designated China as a currency manipulator, but this label was remove prior to signing the Phase One deal with China in 2020 (see Franck, 2020).

The third anti-China argument/statement frame was that **China has unfair trade restrictions** that restrict foreign interactions with Chinese markets. This includes non-trade-specific monetary barriers, such as restricting American companies from partnering with or investing in Chinese companies. A key actor discussed with this frame were inter-government organizations, particularly the World Trade Organization (WTO). For example, several news organizations covered a 2012 WTO decision in favor of the United States, including *Los Angeles Times* (the piece was also republished in other newspapers, like West Virginia's *Charleston Gazette*): "On Friday, a WTO panel largely sided with the U.S. and recommended China bring its policies in compliance with anti-dumping rules. U.S. officials said the Chinese duties affected vehicles manufactured in California and nine other states" (Puzzanghera, May 23, 2014). It's worth noting, both China and the United States have brought cases to the WTO against one another for unfair trade practices (Scott & Jung, 2019).

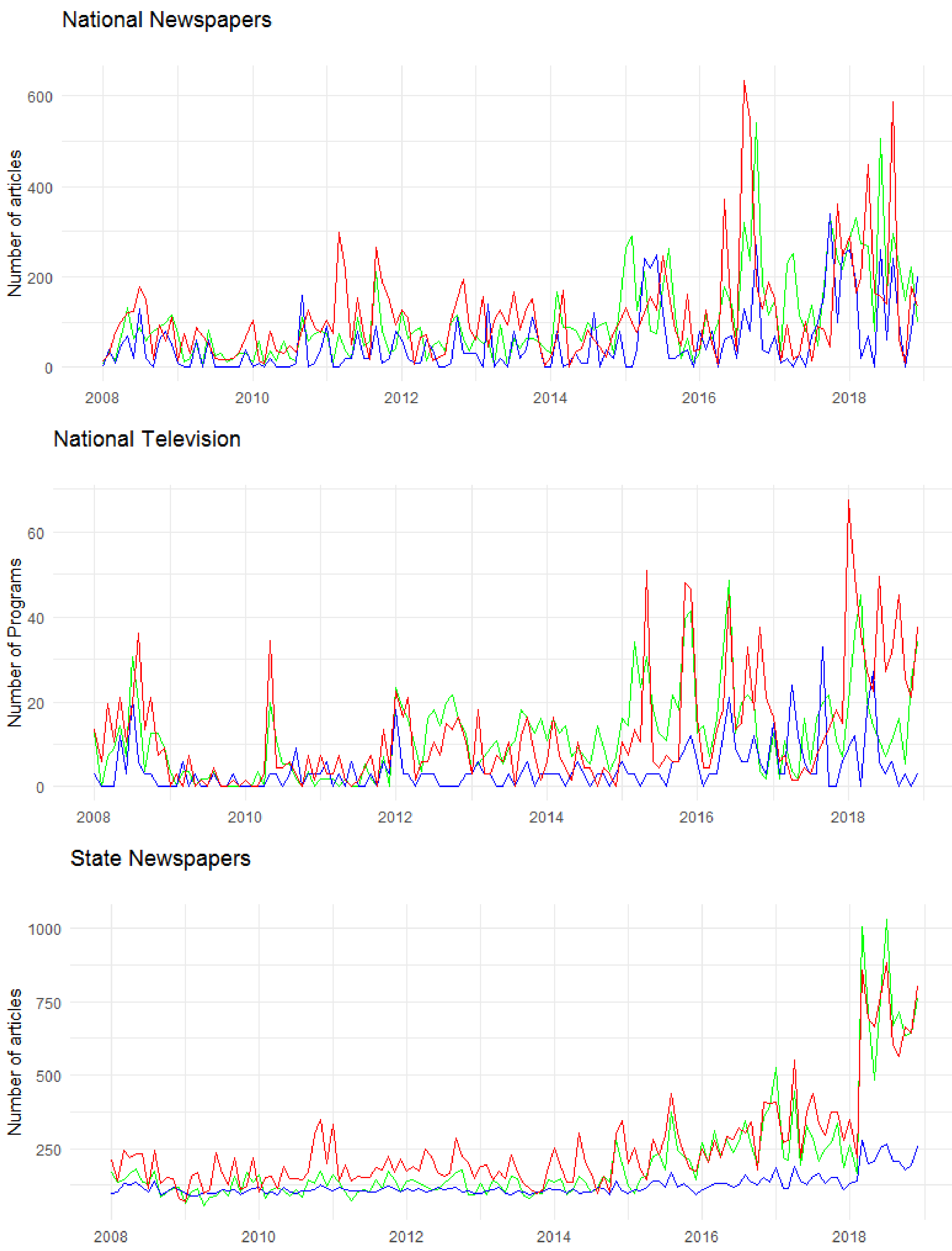
The fourth and final argument/story frame is that **Chinese products are of low-quality**. This demand-oriented frame parallels the last anti-trade frame (that the U.S. depends too much on Chinese goods) but focuses on the quality of the goods rather than the quantity purchased by American consumers. News stories using this frame criticized several made-in-China products, including lead paint in toys and food contamination, including pet food (Pous, 2012). One

[47] It is worth noting that Bergsten and Gagnon (2017) still show a trade shock existed independent of the currency manipulation.

Detroit News article, for example, highlighted concerns regarding contaminated Chinese medication: “During the past year, a long list of consumer items imported from China such as pet food, toothpaste, children's toys, cribs and seafood have all been deemed tainted by U.S. authorities. Two separate Chinese firms sent contaminated wheat protein that was used to make pet food” (*The Detroit Times*, 2008). The FDA was a frequently mentioned regulatory body in news stories using this frame.

Figure 4 displays the number of articles using each frame in national newspapers, national television programs, and state newspapers. In this time frame, there is a notable upward trend in the overall number of articles published or produced about U.S.-China trade. In all three media types (national newspapers, television programs, and state newspapers), news stories using anti-trade frames were the least frequent. In national news media, attention notably increases after 2015. By contrast, local newspapers begin to produce more articles about U.S.-China trade using pro-trade and anti-China in 2018, once President Trump began imposing new tariffs on Chinese exports sold in the United States.

Figure 4: Time Series of Story Frames in News Stories about U.S.-China Trade, 2008-2018



—(green) pro-trade | —(blue) anti-trade | —(red) anti-China

The national news media has several notable temporal spikes. For example, in 2009, President Obama imposed tariffs on Chinese tires which received considerable attention. In early of 2010, China began allowing its currency (the Renminbi; the yuan is the unit of currency) to increase its values in hopes of placating U.S. complaints that China was undervaluing its currency. Spikes in 2015 can be attributed to discussions about the Trans-Pacific Partnership, a substantial Chinese stock bubble burst in June, and discussions of China during the early months of the 2016 Trump campaign. Since 2016, news media coverage of U.S.-China trade has continued to increase and will likely continue to increase so long as the trade dispute persists.

Chapter 6: National VAR

In this chapter, I focus on a national-level analysis of the China trade shock, news coverage of U.S.-China trade and public opinion about the economy and President. For this analysis, I use a vector auto-regression model, a multi-variate time series model used to understand the temporal relationship between variables (Wells et al., 2019). Time series models are popular in political communication because they allow for a temporal consideration of variables with relatively few pre-emptive assumptions about the data.

Data Construction

The temporal unit of analysis in this model is a month. For this analysis, my time range is from January 1, 2008 to December 31, 2018 (11 years), resulting in a time series with 132 months. Fourteen variables were included in the model; these can be grouped into three categories: two economic variables, six news variables, and six public opinion variables.

Economic variables:

1. Import penetration: Chinese import penetration into the United States
2. Manufacturing jobs: The number of manufacturing jobs in the United States (in thousands)

News variables:

3. National newspaper articles with pro-trade frames: A monthly count of national newspaper articles about U.S.-China trade with pro-trade frames.
4. National newspaper articles with anti-trade frames: A monthly count of national newspaper articles about U.S.-China trade with anti-trade frames.
5. National newspaper articles with anti-China frames: A monthly count of national newspaper articles about U.S.-China trade with anti-China frames.
6. National television programs with pro-trade frames: A monthly count of national broadcast programs about U.S.-China trade with pro-trade frames.

7. National television programs with anti-trade frames: A monthly count of national broadcast programs about U.S.-China trade with anti-trade frames.
8. National television programs with anti-China frames: A monthly count of national broadcast programs about U.S.-China trade with anti-China frames.

Public opinion variables:[48]

9. Public opinion among Democrats about job availabilities: A latent time series variable of public opinion among self-identifying Democrats about job availability in their local area/community.
10. Public opinion among Republicans about job availabilities: A latent time series variable of public opinion among self-identifying Republicans about job availability in their local area/community.
11. Presidential job approval among Democrats: A latent time series of presidential job approval among self-identifying Democrats.
12. Presidential job approval among Republicans: A latent time series of presidential job approval among self-identifying Republicans.
13. Public opinion among Democrats about President's handling of the economy: A latent time series of public opinion among self-identifying Democrats about the President's handling of the economy.
14. Public opinion among Democrats about President's handling of the economy: A latent time series of public opinion among self-identifying Democrats about the President's handling of the economy.

In addition to these endogenous variables, I also included two exogenous variables a dummy variable for President Barack Obama (2009-2016), and President Donald Trump (2017-2018).[49]

[48] A correlations test suggested that the six public opinion variables were not strongly correlated. For full results, please see Appendix B.

[49] Although a dummy variable for President George W. Bush was previously included, it did not contribute to the model.

Descriptive Analysis

During the time frame of this study, the United States economy suffered and was slowly recovering from the 2008 Great Recession, which began in the states on December 2007, as reported by the National Bureau of Economic Research in December 2008 (Isidore, 2008). Manufacturing was one of the first sectors to suffer from the recession, which exasperated an already downward trend in manufacturing employment; as a result, manufacturing has not recovered from the recession the way that other sectors have (Monthly Labor Review, 2008). Figure 5 displays a time series of manufacturing employment in the United States.

Figure 5: Manufacturing Jobs in the United States

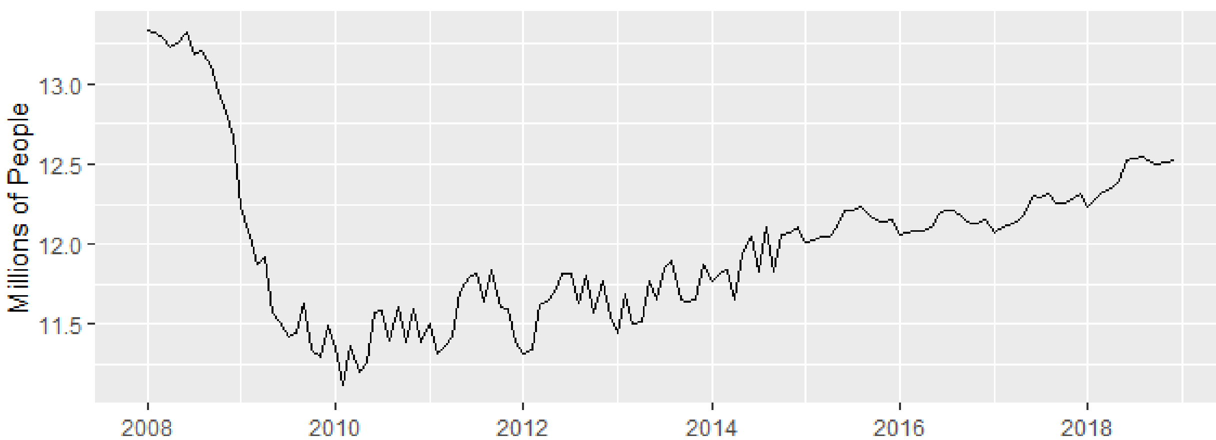
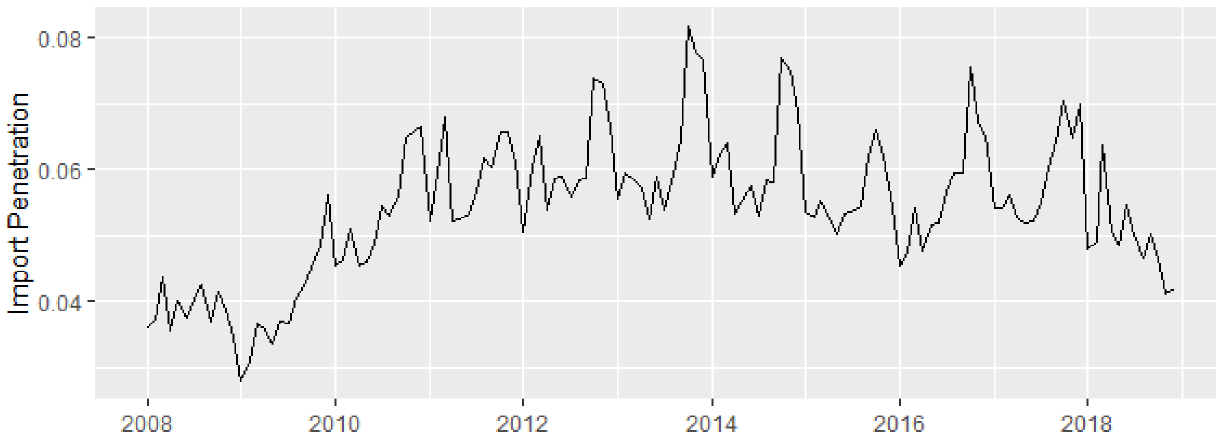


Figure 6 displays Chinese import penetration into the United States. The yearly spike is likely attributable to the sales of iPhones.

Figure 6: Chinese Import Penetration into the United States



Vector Auto-Regression Model

To construct the Vector-Autoregression Model, I first, tested all the time series for non-stationarity, as VAR models require variables to be stationary. Univariate ARIMA models showed that seven time series were integrated:[50] import penetration, manufacturing job availability, pro-trade newspapers, anti-trade newspapers, anti-China newspapers, perception of local job availabilities, and public opinion of how the President handles the economy. This was confirmed with augmented Dicky-Fuller tests. Given that multiple time series variables were non-stationary, I conducted a cointegration test using the Johansen method (Johansen, 2002); no cointegrated relationships were found.[51] As there were no cointegrated relationships, I first-differenced all seven integrated time series to prepare the data for VAR modeling. In addition to this, the import penetration and manufacturing employment variable had a 12-month seasonal

[50] For the purposes of this manuscript, integrated is synonymous with "non-stationary."

[51] One advantage of the Johansen method is that it can identify cointegrated relationships for more than two variables. One disadvantage of the Johansen method is that it is biased towards finding cointegration (Cheung & Lai, 1993); however, in this circumstance, this disadvantage ensures that the integrated time series are not cointegrated.

component (see Figure 5 and 6); these were detrended to isolate the underlying data-generating process (no other variables had a seasonal component).

Next, I determined the appropriate lag for the model using the Akaike Information Criteria (AIC) measure to test models between a lag of 1 and 10; this test recommended a model with six lags (AIC = -3.4058).

I then constructed the VAR(6) using the vars package in R (Pfaff, 2008). For the full model, please see Appendix C. As VAR models are reduced-form models, coefficients are difficult to interpret relative to one another (Benati & Surico, 2009). To better understand the relationship between variables, my analysis will focus on two techniques that build on the VAR model: Granger causality tests and impulse response functions (IRFs).[52] Table 3 displays the results of the Granger causality tests between variables.

[52] The Granger causality tests and IRF graphs focus on endogenous variables; it is worth noting that the Trump dummy variable was statistically significant in the VAR results as related to Presidential approval.

Table 9. Granger Causality Tests of Economic, News, and Public Opinion Variables, VAR(6)

Granger Causality Relationship	X^2	p-value
Import Penetration → Manufacturing Jobs	1.93	0.08
Perceptions of Local Jobs Available		
Newspaper, Pro-Trade Frame → Local Jobs Opinion, Dem.	1.71	0.125
Newspaper, Anti-Trade Frame → Local Jobs Opinion, Dem.	1.79	0.107
Newspaper, Anti-China Frame → Local Jobs Opinion, Dem.	0.20	0.977
TV News, Pro-Trade Frame → Local Jobs Opinion, Dem.	0.63	0.706
TV News, Anti-Trade Frame → Local Jobs Opinion, Dem.	1.97	0.06
TV News, Anti-China Frame → Local Jobs Opinion, Dem.	0.53	0.786
Import Penetration → Local Jobs Opinion, Dem.	0.74	0.622
Manufacturing Jobs → Local Jobs Opinion, Dem.	0.69	0.651
Newspaper, Pro-Trade Frame → Local Jobs Opinion, Rep.	1.51	0.178
Newspaper, Anti-Trade Frame → Local Jobs Opinion, Rep.	3.10	0.008**
Newspaper, Anti-China Frame → Local Jobs Opinion, Rep.	0.20	0.976
TV News, Pro-Trade Frame → Local Jobs Opinion, Rep.	1.42	0.211
TV News, Anti-Trade Frame → Local Jobs Opinion, Rep.	1.66	0.136
TV News, Anti-China Frame → Local Jobs Opinion, Rep.	1.10	0.366
Import Penetration → Local Jobs Opinion, Rep.	1.36	0.239
Manufacturing Jobs → Local Jobs Opinion, Rep.	2.04	0.065
Perceptions of how the President is Handling the Economy		
Newspaper, Pro-Trade Frame → Pres. Handles the Economy, Dem.	0.81	0.567
Newspaper, Anti-Trade Frame → Pres. Handles the Economy, Dem.	0.62	0.714
Newspaper, Anti-China Frame → Pres. Handles the Economy, Dem.	0.21	0.971
TV News, Pro-Trade Frame → Pres. Handles the Economy, Dem.	1.19	0.314
TV News, Anti-Trade Frame → Pres. Handles the Economy, Dem.	0.41	0.869
TV News, Anti-China Frame → Pres. Handles the Economy, Dem.	0.94	0.463
Import Penetration → Pres. Handles the Economy, Dem.	1.16	0.330
Manufacturing Jobs → Pres. Handles the Economy, Dem.	0.55	0.771
Local Job Opinion, Dem → Pres. Handles the Economy, Dem.	0.87	0.523
Newspaper, Pro-Trade Frame → Pres. Handles the Economy, Rep.	0.47	0.828
Newspaper, Anti-Trade Frame → Pres. Handles the Economy, Rep.	0.89	0.505
Newspaper, Anti-China Frame → Pres. Handles the Economy, Rep.	1.96	0.07
TV News, Pro-Trade Frame → Pres. Handles the Economy, Rep.	1.65	0.141
TV News, Anti-Trade Frame → Pres. Handles the Economy, Rep.	2.37	0.034*

TV News, Anti-China Frame → Pres. Handles the Economy, Rep.	1.95	0.095
Import Penetration → Pres. Handles the Economy, Rep.	1.39	0.221
Manufacturing Jobs → Pres. Handles the Economy, Rep.	3.42	0.003**
Local Job Opinion, Rep → Pres. Handles the Economy, Rep.	0.66	0.679
Presidential Job Approval		
Newspaper, Pro-Trade Frame → Presidential Job Approval, Dem.	0.66	0.681
Newspaper, Anti-Trade Frame → Presidential Job Approval, Dem.	1.33	0.248
Newspaper, Anti-China Frame → Presidential Job Approval, Dem.	0.20	0.976
TV News, Pro-Trade Frame → Presidential Job Approval, Dem.	0.21	0.973
TV News, Anti-Trade Frame → Presidential Job Approval, Dem.	0.25	0.957
TV News, Anti-China Frame → Presidential Job Approval, Dem.	0.30	0.937
Import Penetration → Presidential Job Approval, Dem.	0.79	0.576
Manufacturing Jobs → Presidential Job Approval, Dem.	4.94	<0.001***
Newspaper, Pro-Trade Frame → Presidential Job Approval, Rep.	0.45	0.839
Newspaper, Anti-Trade Frame → Presidential Job Approval, Rep.	3.96	< 0.001***
Newspaper, Anti-China Frame → Presidential Job Approval, Rep.	2.91	0.011*
TV News, Pro-Trade Frame → Presidential Job Approval, Rep.	0.14	0.991
TV News, Anti-Trade Frame → Presidential Job Approval, Rep.	0.33	0.918
TV News, Anti-China Frame → Presidential Job Approval, Rep.	0.21	0.971
Import Penetration → Presidential Job Approval, Rep.	0.58	0.746
Manufacturing Jobs → Presidential Job Approval, Rep.	3.31	0.005**

Results of this analysis suggest that anti-trade and anti-China frames in news media and the number of manufacturing jobs available Granger caused Republican's opinions about jobs in the local area and their opinions about the President, both in his broader "job" and specifically with handling the economy. The number of manufacturing jobs did Granger cause perceptions of the President, but no other variables had a statistically significant Granger causality relationship.[53]

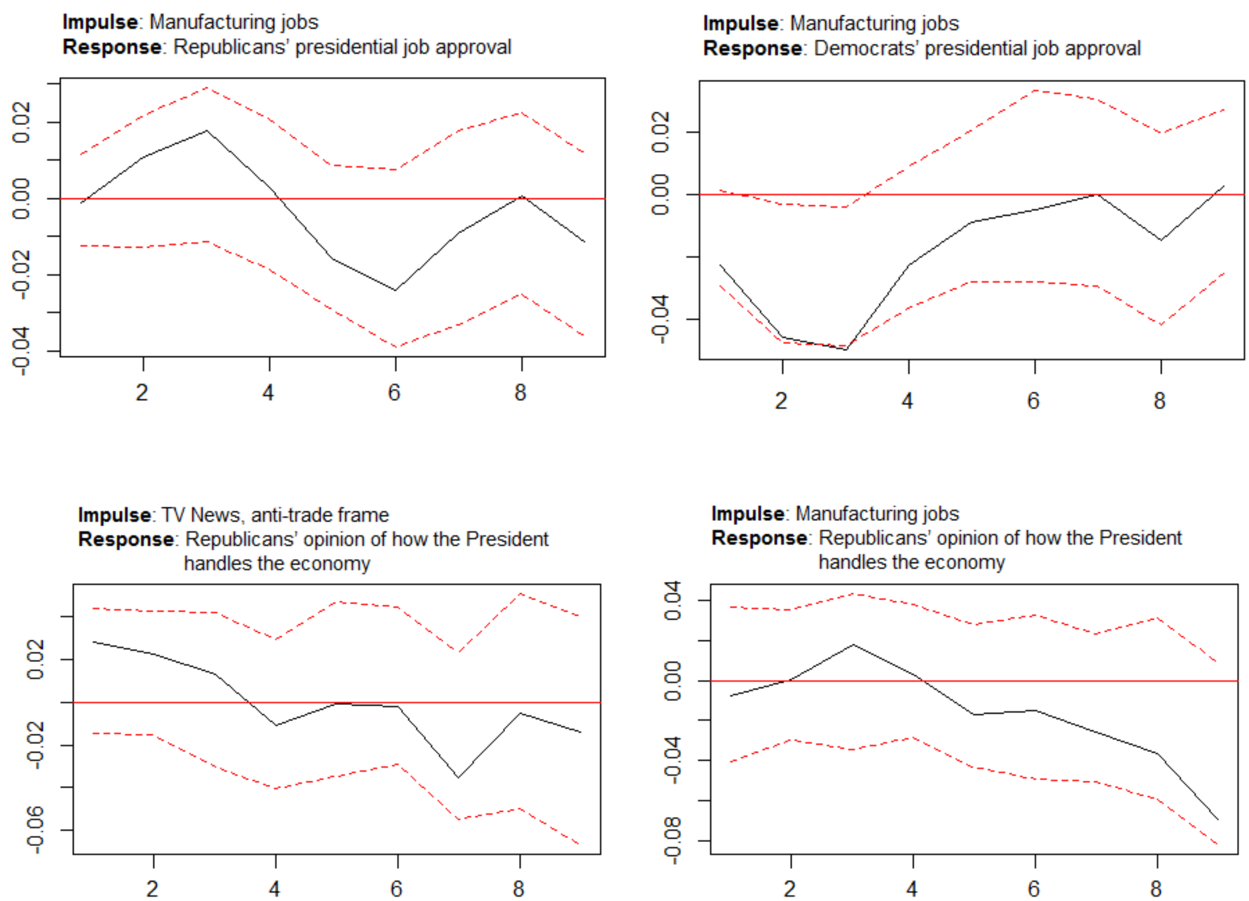
Impulse Response Functions

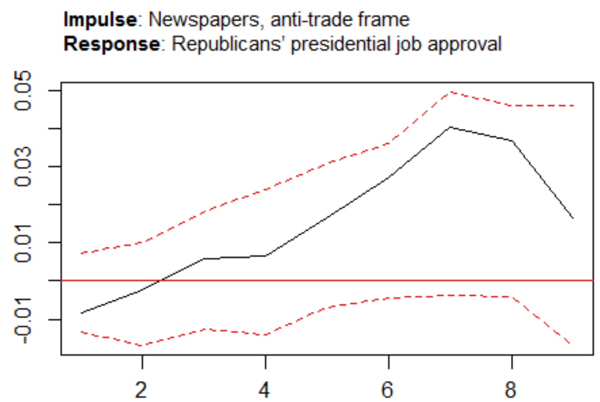
Following the Granger causality results, I ran Impulse Response Function (IRF) graphs, which are a more rigorous test of the relationship between two time series, controlling for all

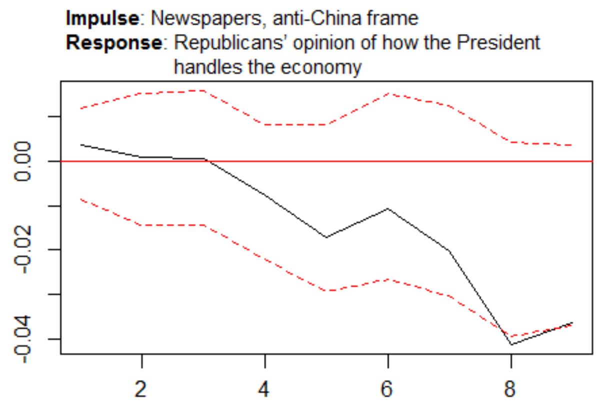
[53] The controls for the Obama Administration and the Trump Administration were not statistically significant

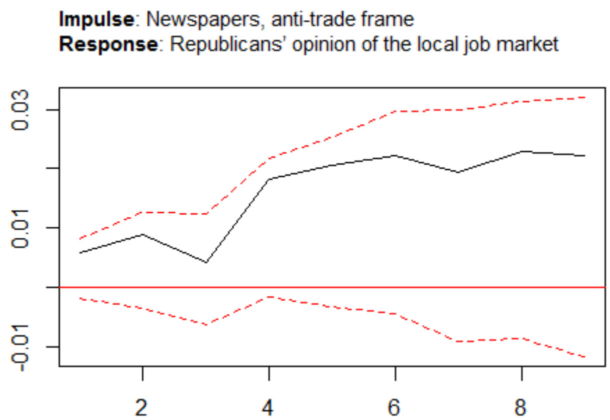
other variables in the model and with a greater consideration of the lags in the model (Dufour & Tessier, 1993). Unfortunately, nearly all of the tested relationships previously identified through the Granger causality test did not produce meaningful IRF results, which the exception of one relationship: manufacturing jobs Granger caused presidential job approval among Democrats, and this relationship is significant and negative at a lag of two and three (see Figure 7).

Figure 7. National VAR Impulse Response Functions









Discussion

Though the Granger causality hinted at some statistically significant relationships, these disappeared in the impulse response functions. I therefore did not find evidence for H1A, which proposed that a national-level China Shock would be related to lower perceptions of the local job market. Nor did I find evidence for H1C, which proposed that a national China shock would be related to lower perceptions of the President. I also did not find evidence for H2A or H2B, which suggested that news media would be shaped by a China shock, or for H3A-H3D, the media influence hypotheses. I did find that shocking manufacturing jobs did decrease perceptions of how well the President was doing his job among Democrats.

These results provide scant evidence of a relationship between economic trends, news media, and public opinion. There was one identifiable relationship: an increase in manufacturing jobs decreased Democrats' presidential approval, suggesting that there may be differences in how Democrats and Republicans' perceive the manufacturing industry: increased manufacturing employment decreases Democrats' support for the President, while manufacturing employment may be perceived more positively by Republicans. However, I did not find evidence of a national China shock, nor did I find evidence that manufacturing employment, news media, and public opinion were related at the national-level.

One explanation for the lack of relationships may be that a national-level analysis obfuscated important variations geographically, both in terms of economic factors and local news coverage. In other words, the relationship between economic factors, news media, and public opinion may vary by a states' unique socioeconomic circumstances over the past decade. If there were to be relationships at the state-level that disappear when aggregated nationally, my findings would indicate a Simpson's paradox, which occurs when a relationship found between variables across groups is obscured when the groups (in this case, states) are combined (Blyth, 1972). In the following chapter, I rigorously examine how state-level variations contribute to how economic and news factors influence public opinion.

Chapter 7: State-Level mlVAR

In this chapter, I focus on a state-level analysis of the China trade shock, news coverage of U.S.-China trade, and the public opinion variables. One reason why it is worth considering state-level variation is because of the highly localized nature of both the China shock and the media ecology: some geographic regions are more greatly impacted by U.S.-China trade (either as exporters or importers) than others, and state vary greatly in their news ecology. The goal of this chapter is to understand the influences of the economy and news media on public opinion when accounting for state-level variation. I lay out this analysis in two steps: first, I construct and interpret the multi-level Vector Auto-Regression. Next, I illustrate regional differences by focusing on three state-level cases: Wisconsin, Florida, and New Hampshire. For these cases, I validate the multi-level Vector Autoregression (mlVAR) results with state-specific VAR models.

Data Construction

The temporal unit of analysis in this model is a month. For this analysis, my time range is from January 1, 2008 to December 31, 2008 (11 years), paralleling the national VAR analysis done in Chapter 6. In addition to the 14 variables included in the national VAR, I also include 3 additional news variables for state-level newspapers using the pro-trade frame, the anti-trade frame, or the anti-China frame, resulting in a total of 17 variables, listed below:

Economic

1. Import penetration
2. Manufacturing jobs (in thousands of jobs)

News variables:

3. National pro-trade newspaper articles
4. National anti-trade newspaper articles
5. National anti-China newspaper articles
6. National pro-trade TV program

7. National anti-trade TV program
8. National anti-China TV program
9. Local newspaper articles with pro-trade frames
10. Local newspaper articles with anti-trade frames
11. Local newspaper articles with anti-China frames

Public opinion variables:

12. Public opinion among Democrats in the state about job availabilities
13. Public opinion among Republicans in the state about job availabilities
14. Presidential job approval among Democrats in the state
15. Presidential job approval among Republicans in the state
16. Public opinion among Democrats in the state about President's handling of the economy
17. Public opinion among Democrats in the state about President's handling of the economy

Multi-Level Vector Auto-Regression

To construct the multi-level vector auto-regression ("mlVAR"), I use the mlVAR() package in R (Epskamp, Deserno & Bringmann, 2019). Though this package was originally constructed for the analysis of participants within a survey, I extend its used to construct a fixed-effect model for states. Like the standard VAR model, a prerequisite of the mlVAR is stationarity among the time series variables, resulting in 556 augmented Dicky-Fuller tests (11 x 50 for the state-level variables, and 6 for the national-level news frame variables). Slightly over 80% (n = 449) had a unit-root and were first-differenced. Fourteen of the state-level import penetration time series variables had 12-month seasonal components that were detrended and six of the state-level manufacturing jobs had 12-motnth seasonal components that were detrended.[54]

[54] States with a seasonal component in import penetration Alaska, Louisiana, Nevada, North Dakota, Ohio, Oklahoma, Oregon, Rhode Island, Tennessee, Texas, Virginia, Washington, West Virginia, and Wyoming. States with a seasonal component in manufacturing jobs: Alaska, California, Maine, Minnesota, Oregon, and Wisconsin.

Once the data were pre-processed, I ran tests to identify the appropriate lag using the mlVARcompare() function, which compares different mlVAR models by identifying the optimal AIC or BIC for each variable's reduced model. Of the 17 variables, in a comparison of 10 models with p = 1 to 10, a lag of 6 was optimal for 8 of the variables.

The mlVAR() function reports aggregate fixed temporal effects for each variable at the 6th lag, which are presented in Table 10. However, like the standard VAR, the coefficients of the reduced models of the multi-level VAR are difficult to interpret; I therefore focus my interpretation exclusively on the statistical significance and directionality (for the full model, please see Appendix D).

Table 10. Temporal Effects of Economic, News, and Public Opinion Variables, mlVAR(6)

Relationship	**Coeff.**	**SE**	**p-value**
Import Penetration → Manufacturing Jobs	-0.00	0.00	0.009
Manufacturing Jobs → News Media			
Manufacturing Jobs → National NP, Pro-Trade Frames	0.36	0.17	0.059
Manufacturing Jobs → National NP, Anti-Trade Frames	-0.08	0.19	0.675
Manufacturing Jobs → National NP, Anti-China Frames	-0.45	0.05	0.000
Manufacturing Jobs → National TV, Pro-Trade Frames	0.11	0.18	0.516
Manufacturing Jobs → National TV, Anti-Trade Frames	0.30	0.18	0.868
Manufacturing Jobs → National TV, Anti-China Frames	0.00	0.19	0.998
Manufacturing Jobs → State NP, Pro-Trade Frames	0.85	0.11	0.000
Manufacturing Jobs → State NP, Anti-Trade Frames	-0.43	0.18	0.017
Manufacturing Jobs → State NP, Anti-China Frames	-0.20	0.16	0.021
Perceptions of Local Jobs Available			
National NP, Pro-Trade Frame → Local Jobs Opinion, Dem.	0.04	0.01	0.000
National NP, Anti-Trade Frame → Local Jobs Opinion, Dem.	0.06	0.01	<0.000
National NP, Anti-China Frame → Local Jobs Opinion, Dem.	-0.07	0.02	<0.000
National TV, Pro-Trade Frame → Local Jobs Opinion, Dem.	0.06	0.01	<0.000
National TV, Anti-Trade Frame → Local Jobs Opinion, Dem.	0.00	0.01	0.855
National TV, Anti-China Frame → Local Jobs Opinion, Dem.	0.01	0.01	0.525

State NP, Pro-Trade Frame → Local Jobs Opinion, Dem.	0.01	0.01	0.472
State NP, Anti-Trade Frame → Local Jobs Opinion, Dem.	0.00	0.01	0.926
State NP, Anti-China Frame → Local Jobs Opinion, Dem.	0.01	0.01	0.571
Import Penetration → Local Jobs Opinion, Dem.	0.03	0.01	0.101
Manufacturing Jobs → Local Jobs Opinion, Dem.	-0.06	0.09	0.515
National NP, Pro-Trade Frame → Local Jobs Opinion, Rep.	0.06	0.01	0.076
National NP, Anti-Trade Frame → Local Jobs Opinion, Rep.	-0.01	0.01	0.563
National NP, Anti-China Frame → Local Jobs Opinion, Rep.	-0.04	0.01	<0.000
TV News, Pro-Trade Frame → Local Jobs Opinion, Rep.	-0.01	0.01	0.429
TV News, Anti-Trade Frame → Local Jobs Opinion, Rep.	-0.00	0.01	0.749
TV News, Anti-China Frame → Local Jobs Opinion, Rep.	-0.01	0.01	0.028
State NP, Pro-Trade Frame → Local Jobs Opinion, Rep.	0.01	0.01	0.005
State NP, Anti-Trade Frame → Local Jobs Opinion, Rep.	-0.06	0.01	0.563
State NP, Anti-Trade Frame → Local Jobs Opinion, Rep.	-0.04	0.01	0.001
Import Penetration → Local Jobs Opinion, Rep.	-0.02	0.01	0.054
Manufacturing Jobs → Local Jobs Opinion, Rep.	0.33	0.11	0.002
Perceptions of how the President is Handling the Economy			
National NP, Pro-Trade Frame → Pres. Handles the Economy, Dem.	-0.06	0.02	0.005
National NP, Anti-Trade Frame → Pres. Handles the Economy, Dem.	-0.07	0.02	<0.000
National NP, Anti-China Frame → Pres. Handles the Economy, Dem.	0.01	0.04	0.659
National TV, Pro-Trade Frame → Pres. Handles the Economy, Dem.	0.05	0.02	0.02
National TV, Anti-Trade Frame → Pres. Handles the Economy, Dem.	0.01	0.02	0.646
National TV, Anti-China Frame → Pres. Handles the Economy, Dem.	0.01	0.02	0.738
State NP, Pro-Trade Frame → Pres. Handles the Economy, Dem.	-0.03	0.02	0.131
State NP, Anti-Trade Frame → Pres. Handles the Economy, Dem.	0.02	0.02	0.200
State NP, Anti-China Frame → Pres. Handles the Economy, Dem.	-0.02	0.02	0.201
Import Penetration → Pres. Handles the Economy, Dem.	-0.06	0.02	0.003
Manufacturing Jobs → Pres. Handles the Economy, Dem.	-0.14	0.01	0.000
Local Job Opinion, Dem → Pres. Handles the Economy, Dem.	-0.01	0.02	0.729
National NP, Pro-Trade Frame → Pres. Handles the Economy, Rep.	0.04	0.02	0.082
National NP, Anti-Trade Frame → Pres. Handles the Economy, Rep.	0.03	0.02	0.010
National NP, Anti-China Frame → Pres. Handles the Economy, Rep.	-0.02	0.04	0.564
National TV, Pro-Trade Frame → Pres. Handles the Economy, Rep.	-0.03	0.02	0.181
National TV, Anti-Trade Frame → Pres. Handles the Economy, Rep.	0.00	0.02	0.996

National TV, Anti-China Frame → Pres. Handles the Economy, Rep.	-0.01	0.02	0.449
State NP, Pro-Trade Frame → Pres. Handles the Economy, Rep.	0.02	0.02	0.402
State NP, Anti-Trade Frame → Pres. Handles the Economy, Rep.	0.00	0.02	0.953
State NP, Anti-China Frame → Pres. Handles the Economy, Rep.	0.01	0.02	0.569
Import Penetration → Pres. Handles the Economy, Rep.	-0.01	0.02	0.823
Manufacturing Jobs → Pres. Handles the Economy, Rep.	-0.04	0.02	0.045
Local Job Opinion, Rep → Pres. Handles the Economy, Rep.	0.06	0.02	0.001
Presidential Job Approval			
National NP, Pro-Trade Frame → Presidential Job Approval, Dem.	-0.08	0.02	0.000
National NP, Anti-Trade Frame → Presidential Job Approval, Dem.	-0.11	0.01	0.796
National NP, Anti-China Frame → Presidential Job Approval, Dem.	0.04	0.03	0.218
National TV, Pro-Trade Frame → Presidential Job Approval, Dem.	-0.12	0.02	<0.000
National TV, Anti-Trade Frame → Presidential Job Approval, Dem.	-0.02	0.01	0.122
National TV, Anti-China Frame → Presidential Job Approval, Dem.	-0.01	0.01	0.735
State NP, Pro-Trade Frame → Presidential Job Approval, Dem.	-0.06	0.02	<0.000
State NP, Anti-Trade Frame → Presidential Job Approval, Dem.	-0.00	0.01	0.962
State NP, Anti-China Frame → Presidential Job Approval, Dem.	-0.05	0.02	0.001
Import Penetration → Presidential Job Approval, Dem.	-0.01	0.02	0.700
Manufacturing Jobs → Presidential Job Approval, Dem.	-0.28	0.02	0.000
Local Job Opinion, Dem → Presidential Job Approval, Dem.	-0.08	0.01	0.000
Pres. Handles the Economy, Dem.→ Presidential Job Approval, Dem.	0.02	0.01	0.053
National NP, Pro-Trade Frame → Presidential Job Approval, Rep.	0.08	0.02	0.000
National NP, Anti-Trade Frame → Presidential Job Approval, Rep.	0.02	0.02	0.013
National NP, Anti-China Frame → Presidential Job Approval, Rep.	-0.01	0.03	0.000
National TV, Pro-Trade Frame → Presidential Job Approval, Rep.	0.15	0.02	<0.000
National TV, Anti-Trade Frame → Presidential Job Approval, Rep.	0.04	0.01	0.004
National TV, Anti-China Frame → Presidential Job Approval, Rep.	-0.02	0.01	0.016
State NP, Pro-Trade Frame → Presidential Job Approval, Rep.	0.04	0.01	0.061
State NP, Anti-Trade Frame → Presidential Job Approval, Rep.	0.00	0.01	0.787
State NP, Anti-China Frame → Presidential Job Approval, Rep.	-0.05	0.01	<0.000
Import Penetration → Presidential Job Approval, Rep.	-0.03	0.02	0.048
Manufacturing Jobs → Presidential Job Approval, Rep.	0.26	0.02	<0.000
Local Job Opinion, Rep → Presidential Job Approval, Rep.	0.09	0.01	<0.000
Pres. Handles the Economy, Rep → Presidential Job Approval, Rep.	-0.01	0.01	0.462

Let's take each variable individually.

First, the results of the model do find a statistically significant China shock phenomenon: as import penetration increases, manufacturing employment decreases.

Manufacturing Job Loss and News Coverage. Manufacturing employment seemed to influence certain news layers. The most notable relationship is that between state news media and manufacturing employment: more manufacturing jobs increased state-level newspaper coverage using pro-trade frames (coeff = 0.85, $p < 0.000$), while fewer manufacturing jobs increased state-level newspaper coverage using anti-trade frames (coeff = -0.43, $p < 0.05$) and anti-China frames (coeff = 0.20, $p < 0.05$). Fewer manufacturing jobs also increased national newspaper use of anti-China frames (coeff = 0.45, $p < 0.000$), but no other national-level variables were found. I therefore find some evidence that H2A: manufacturing job loss increased the state media's use of anti-trade frames and anti-China frames, both of which portray U.S.-China trade negatively, and the national newspapers' use of anti-China frames. I also find that manufacturing jobs were positively related to Republicans' perception of the local job market, providing evidence for H1B specifically for Republicans.

Perceptions of Local Jobs Available. Among Democrats, national newspapers, regardless of the frame (pro-trade coefficient = 0.00, $p < 0.001$; anti-trade coeff. = 0.06, $p < 0.01$; anti-China coeff. = -0.07, $p < 0.001$), and pro-trade television programs (coeff. = 0.06, $p < 0.001$) helped explain perceptions of the local job availability. For Republicans, it is not so much the medium as it is the frame itself: anti-China framed content in national newspapers (coeff. = -0.04, $p < 0.001$), national television (coeff. = -0.01, $p < 0.05$), and local newspapers (coeff. = -0.04, $p < 0.01$) all decreased perceptions of local jobs available (pro-trade frames in state-level newspapers also increases perceptions of local jobs available, coeff. = 0.01, $p < 0.01$; this may be related to coverage of trade deals between a state and a Chinese company). For Republicans, more manufacturing jobs increased people's perceptions of jobs available in the local area (coeff. = 0.33, $p < 0.01$); the same was not true of Democrats (coeff. = -0.06, $p = 0.515$).

Perceptions of how the President is Handling the Economy. Among Democrats, national newspapers with pro-trade frames (coeff. = -0.06, $p < 0.01$) and anti-trade frames (coeff. = -0.07, $p < 0.001$) decreased perceptions of how the president was handling the economy. Increased manufacturing jobs and increased import penetration both decreased Democrats' perception that the president was handling the economy well. For Republicans, only national news stories with anti-trade frames (coeff. = 0.03, $p < 0.05$), manufacturing jobs (coeff. = -0.04, $p < 0.05$), and perceptions about local jobs available (coeff. = 0.6, $p < 0.01$), appear to influence people's perceptions of how the President was handling the economy. These relationships were not necessarily in the direction anticipated. For example, counter to H1C, fewer manufacturing jobs appeared to increase Republicans' perception of how the President was handling the economy.

Presidential Job Approval. For Democrats, the use of pro-trade frames in national newspapers (coeff. = -0.08, $p < 0.001$), national broadcast news (coeff. = 0.12, $p < 0.001$), and state newspapers (coeff. = - 0.05, $p < 0.01$) all decreased people's perceptions of the President, as did anti-China frames in state newspapers (coeff. = -0.05, $p < 0.01$) and an increase in manufacturing jobs (coeff. = -0.28, $p < 0.001$). For Republicans, the picture is more complex. National newspaper articles with pro-trade frames (coeff. = 0.08, $p < 0.001$), national television programs with pro-trade frames (coeff. = 0.15, $p < 0.001$), national newspaper articles with anti-trade frames (coeff. = 0.02, $p < 0.05$), and national television programs with anti-trade frames (coeff. = 0.04, $p < 0.01$) increased people's approval of how the President was handling his job. In other words, national news media coverage focusing on U.S.-China trade, whether positive or negative, increased people's perception of the President. On the other hand, anti-China frames in national newspapers (coeff. = -0.01, $p < 0.001$), national television programs (coeff. = 0.02, $p < 0.05$), and state newspapers (coeff. = -0.02, $p < 0.05$). Importantly, increased import penetration decreased Republican's perceptions of the President (coeff. = -0.03, $p < 0.05$) and increased manufacturing jobs increased Republican's perceptions of the President (coeff = 0.26, $p < 0.000$), highlighting the combined influence of both economic and news variables.

The results of this analysis suggest that that both national and state-level news media have the capacity to shape both Democrats' and Republicans' public opinion about the local job market and the President (H3A-D). However, this was not only true of stories framing U.S.-China trade with anti-China or anti-trade frames; pro-trade stories were also related to the public opinion variables. Though state newspapers shaped the Presidents' job approval, the results suggest that frames in national newspaper and television were especially influential for Democrats, while Republicans' public opinion was related to a range of national and state media. This also provides some evidence that there may be differences between how news media influence Republicans' and Democrats' public opinion of the economy and the President.

Importantly, the mlVAR reveals interesting relationships that the national-level VAR did not. Why is that? The primary difference between the national VAR and the fixed-effect mlVAR is that the former aggregates the variables into national averages and constructs one VAR, while the latter effectively constructs a VAR for each state, pools the parameter estimates, and then takes the average (Epskamp, Waldorp, Mõttus & Borsboom, 2018). In other words, the mlVAR considers intra-state relationships between variables in a way that a national VAR cannot.

Case Analyses: A Tale of 3 States

It is beyond the scope of this dissertation to analyze all 50 unique models for each state. However, to illustrate the importance of state-level variation, I will focus on three states: Wisconsin, Florida, and New Hampshire. The purpose of investigating these cases further is not to group the states in any way, nor to compare which state "suffered more" from a trade shock,[55] but rather to emphasize the importance of regional economics and potential media influences. With this in mind, I selected these three states because they differed greatly in their economic dependence on the manufacturing industry (either as a proportion of GSP or of employment): one state that depends heavily on manufacturing (Wisconsin), one state that does not rely substantially on manufacturing (Florida), and one state in the middle (New Hampshire).

To select the cases, I looked at how much manufacturing output contributed to a states' gross state product (GSP) and the proportion of non-agricultural jobs that are manufacturing.[56] The average share of manufacturing jobs that are a share of non-agricultural employment is 8.7 (*SD* = 3.5). The average share of GSP attributable to manufacturing products is 13.1 (*SD* = 8.5). With this context in mind, I selected three states. The first, Wisconsin, had the highest z-score for share of GSP (z = 4.72) and the second-highest z-score for share of employment (z = 2.15). The second, Florida, has one of the lowest z-scores for share of GSP (z = -0.95) and share of employment (z = -0.95). The third case, New Hampshire, is above average in manufacturing as a share of non-agricultural employment (z = 0.44), but below average in manufacturing products as a share of GSP (-0.63).

[55] Such comparisons are divisive and over reductive.

[56] I did not use raw numbers because the number of manufacturing jobs in a state is greatly determined by the size of that state.

Another reason I selected these states is because all three were considered "traditional swing states" and were very closely contested in 2016 (Silver, 2016). During the 2016 election, Wisconsin (47.9% Trump to 46.9% Clinton) and Florida (49.1 to 47.8%) voted for Donald Trump [R]. New Hampshire voted for Hillary Clinton [D] for President (47.6% to 47.2%) but voted in Chris Sununu [R] for Governor (49.0% to 46.7%).

To explore these three cases in greater depth, I run individual VARs for the states to analyze the results using Granger causality tests and Impulse Response Functions. For spatial reasons, I will only present the statistically significant Granger causality results, but the full results can be found in Appendix E.

Wisconsin: A Trade Shocked Manufacturing State

As a major contributor to the GSP and as a key source of employment, manufacturing is an essential industry in the Wisconsin economy. According to the U.S. Bureau of Labor Statistics (2016), manufacturing has been the industry with the highest employment in Wisconsin from 1990 to 2015, and its 7,722 manufacturing firms constitute a whopping 15.89% of non-farm employment in 2019 (National Association of Manufacturers, 2020). Manufacturing output, valued at over $63 billion, is nearly a fifth of the gross state product (18.79%).

Wisconsin's continued reliance on manufacturing differs from other Midwestern states, whose largest industries changed from manufacturing to healthcare in the first decade of the millennium. Though the southeast corner of Wisconsin is considered part of the U.S. "rustbelt," an area that suffered from deindustrialization in the 1980's, most of Wisconsin benefitted from a growing manufacturing industry until the late-1990's. After peaking in 1997, manufacturing became a smaller proportion of the overall number of jobs in the state, from 28% in 1970 to 14% in 2015 (Conroy, Kures, & Chen, 2018); by contrast, healthcare became a larger share of employment from 2000 to 2015. The decline in manufacturing jobs is attributed to a range of factors, including automation and the China Shock.[57] Autor et al. (2016) note that Wisconsin was among the states most impacted politically by the China shock; they also argue that a smaller trade shock would have increased the likelihood that Wisconsin would have voted for a Democratic candidate.[58]

The manufacturing industry in Wisconsin is notable for its diversity: Wisconsin manufactured a range of products, from paper to large machinery. According to a Wisconsin Economic Development Corporation report (2013),[59] electrical equipment manufacturing ($2,706,000,000), converted paper product manufacturing ($2,619,000,000), pulp and paper mills ($2,608,000,000), plastic product manufacturing ($2,598,000,000), and dairy product manufacturing ($2,063,000,000) contributed the most to the 2013 gross state product. Of these, electrical equipment and dairy product manufacturing are considered particularly export competitive (i.e., competitive against other manufacturers in the global market).

Politically, Wisconsin is known as a state with tight races (White, 2020). For the majority of this study's time frame, the Governor of Wisconsin was Scott Walker [R] (he was defeated in 2018 by Tony Evers [D]). Job creation, particularly in manufacturing, was a key issue for Walker. His 2010 signature campaign promise—at a time when manufacturing employment was at a critical low point—was to add 250,000 jobs to the Wisconsin economy (Nelson, 2014).[60]

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[57] As of July 2, 2020, conservative superPAC America First Action was still sharing the misinformation that China is the sole cause of Wisconsin manufacturing job loss (Andrea, 2020)

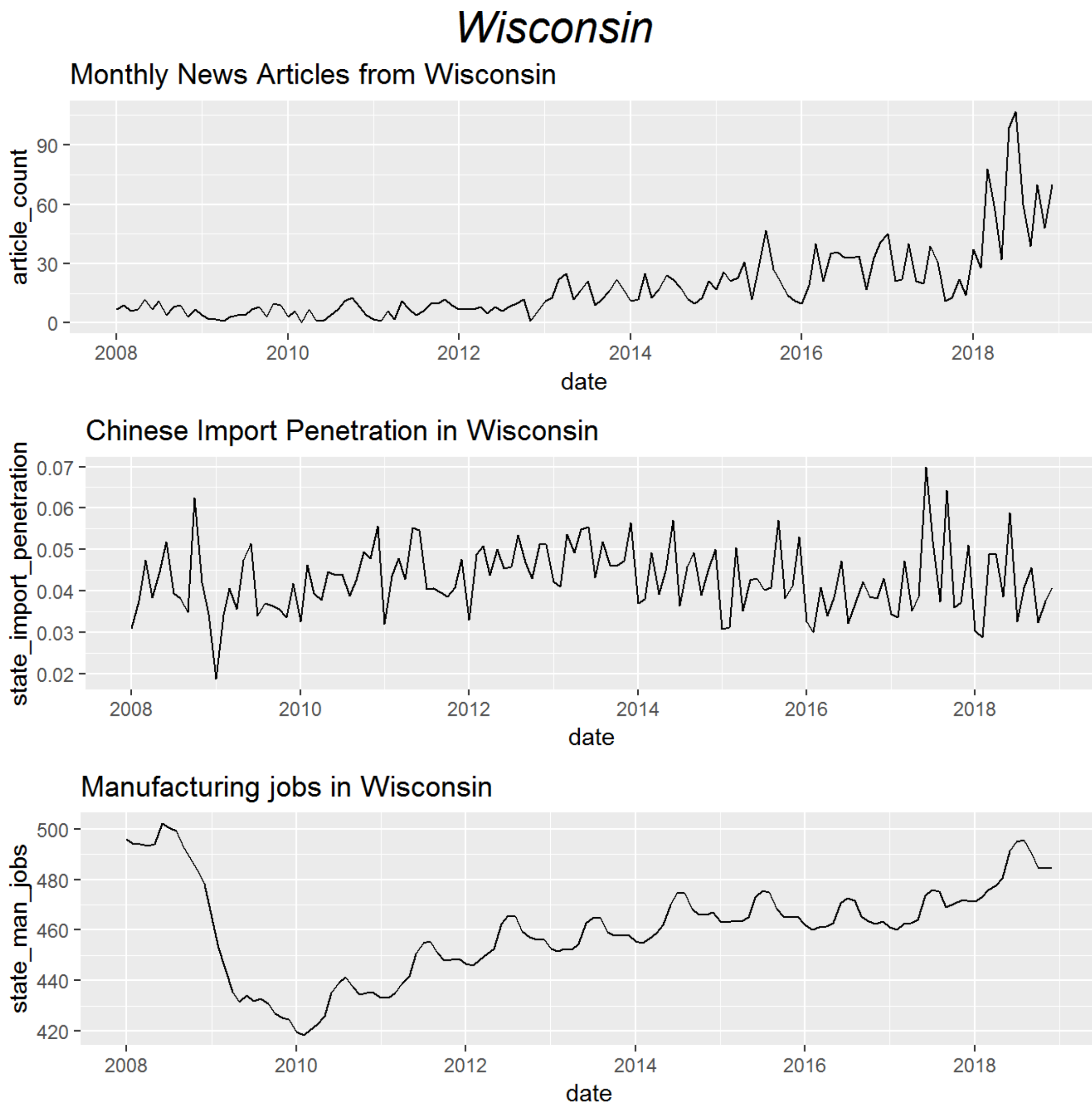
[58] Autor et al.'s (2016) analysis does not consider the other political circumstances surrounding the Clinton-Trump election, focusing exclusively on them as "the Democrat" and "the Republican."

[59] The WEDC is a public-private agency established by then-Governor Walker in 2011. It was tasked with awarding grants and loans to companies to facilitate job creation. The WEDC has been criticized for not properly vetting grant or loan recipients and for awarding millions of dollars to companies who did not create many jobs (Defour, 2015).

[60] During his time in office, Walker added 233,101 jobs to the private sector, though this growth was behind the national average (Johnson, 2019).

Figure 1 displays the number of articles published by Wisconsin newspapers about U.S.-China trade, the import penetration ratio for Wisconsin, and the number of manufacturing jobs.

Figure 8. Wisconsin News Media, Import Penetration, and Manufacturing Employment



Before proceeding, it is worth noting a few trends. Similar to the national trend, Wisconsin news media coverage has an upward trajectory.[61] While there is a steady increase from 2015 to the end of 2017, the substantive spike occurs in 2018—when President Trump announced his tariffs targeting China. The first spike occurs in January 2018, when President Trump imposed tariffs on solar panels and washing machines (China is the world's leading manufacturer of solar panels, see Mullen, 2018). The second, and largest, spike occurs in March 2018, when President Trump applied tariffs to over $50 billion worth of Chinese goods. Unlike national media, news articles in Wisconsin were most likely use pro-trade frames (n = 756) compared to anti-trade (n = 162) or anti-China frames (n = 462).

Wisconsin is one of the states with a 12-month seasonal trend in manufacturing employment. Seasonality is a common temporal feature found in manufacturing-dependent economies because many manufacturing sectors are seasonal (Beaulieu & Miron, 1991). Some of Wisconsin's manufacturing sectors, such as food manufacturing, have seasonal trends (Goomas & Ludwig, 2017).

VAR(3) Model. To construct a VAR model to analyze Wisconsin, I followed the same procedure used to prepare the data for a time series analysis: identify time series that are non-stationary, first-difference non-stationary time series, and detrend seasonal components in the import penetration time series. In the Wisconsin data, 13 variables were non-stationary. Manufacturing employment had a 12-month seasonality pattern that was detrended.

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[61] In the state newspaper corpus, Wisconsin is represented by 9 outlets: Green Bay Press-Gazette (owned by Gannett), Herald Times Reporter (owned by Gannett since 2008), The Waukesha Freeman (owned by Conley Publishing Group), the Milwaukee Journal Sentinel (independently owned until it was purchased by Gannett in 2016), the Post-Crescent (owned by Gannett), the Chippewa Herald (owned by Lee Enterprises), Wisconsin State Journal (owned by Lee Enterprises), The Capital Times (independently owned), and Oshkosh Northwestern (owned by Gannett). Collectively, they published 1,293 articles with relevant excerpts.

Using the AIC (-9.69), I determined that the optimal model had a lag of 3. Once I constructed the VAR(3) model, I ran Granger causality tests between the variables.[62] Table 10 displays the statistically significant results.

Table 11. Statistically Significant Granger Causality Tests for Wisconsin, VAR(3)

Relationship	$\boldsymbol{X^2}$	**p-value**
Import Penetration → Manufacturing Jobs	17.30	0.004
Manufacturing Jobs → Local Job Opinion, Rep.	46.63	0.000
Manufacturing Jobs → State NP, Pro-Trade Frame	11.22	0.047
State NP, Anti-Trade Frame → Local Jobs Opinion, Rep.	16.31	0.006
National TV, Anti-Trade Frame → Local Jobs Opinion, Rep.	37.88	0.000
National TV, Anti-China Frame → Local Jobs Opinion, Rep.	11.98	0.035
State NP, Anti-China Frame → Pres. Handling the Economy, Rep.	10.87	0.045
Local Job Opinion, Rep. → Presidential Job Approval, Rep.	13.61	0.018
National NP, Anti-Trade Frame → Presidential Job Approval, Rep.	17.30	0.009
National NP, Pro-Trade Frame → Pres. Handling the Economy, Dem.	13.42	0.020

First, it is worth noting, in the model, import penetration into Wisconsin Granger caused manufacturing jobs, providing some evidence for the China shock. In addition to this, manufacturing jobs Granger caused people's perceptions of job availability in their local area. The Impulse Response Function for this relationship (see Figure 9) shows that this is an inverse relationship: shocking import penetration decreases the number of manufacturing jobs in Wisconsin; this effect also seems to last for a long time.

[62] This VAR, and all VARs, controlled for the Trump administration and Obama administration as exogenous variables.

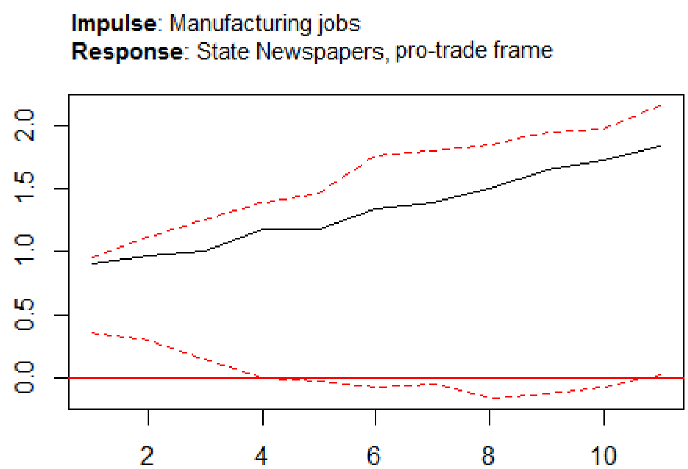
Figure 9. Impulse Response Function for China Shock in WI

While the number of manufacturing jobs Granger caused Republicans' perceptions of jobs available in their local area, manufacturing jobs was not related to other public opinion variables. The Impulse Response Functions in Figure 10 show that increasing manufacturing jobs improves Republican's perceptions of jobs in their local area (right) , but the same is not true for Democrats (left).

Figure 10. Impulse Response Function of Manufacturing jobs on Opinions of the Local Job Market, WI

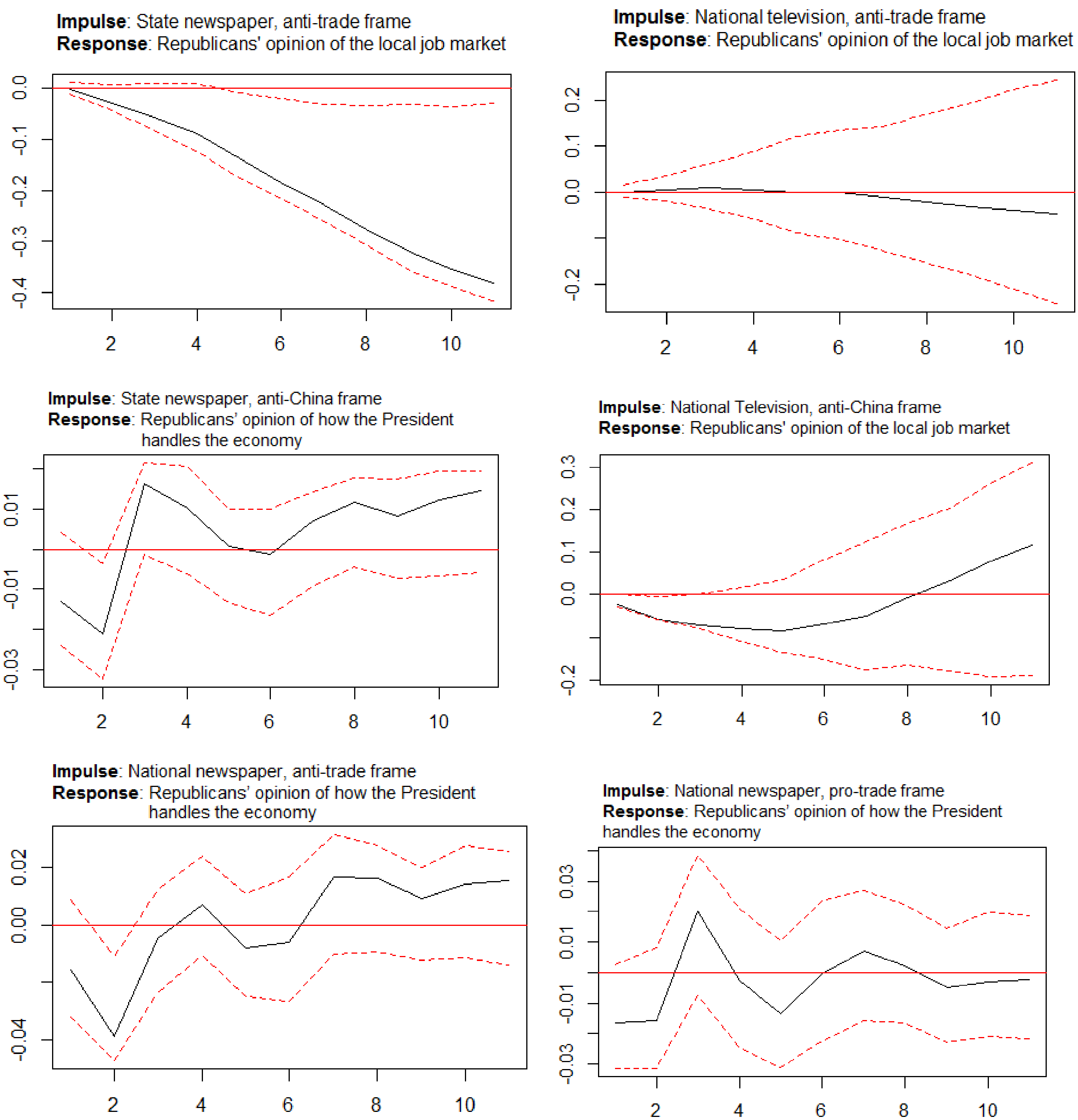
Manufacturing jobs also Granger caused the use of pro-trade frame in Wisconsin news. The impulse response function shows that this relationship is positive: as manufacturing employment increased, stories from state newspapers with pro-trade news frames increased in the first few weeks (see Figure 11). Some of these stories highlighted deals or relationships Wisconsin and Chinese companies or the government (though not necessarily about manufacturing), like in the lead of this *Green Bay Press Gazette* article, "Building relationships for future business opportunities is the goal behind a bipartisan trade mission to China, headed up Wisconsin Lt. Gov. Rebecca Kleefisch" (Phelps, 2014). About 22% of the articles with pro-trade frames mentioned state words (n = 170).

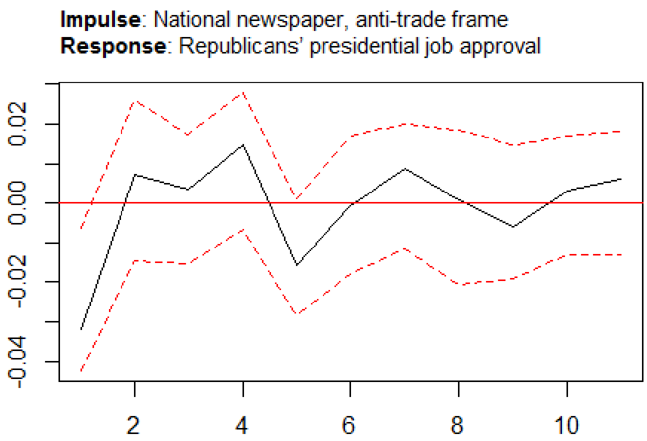
Figure 11. Impulse Response Function of Manufacturing Jobs on pro-trade frames in Wisconsin Newspapers

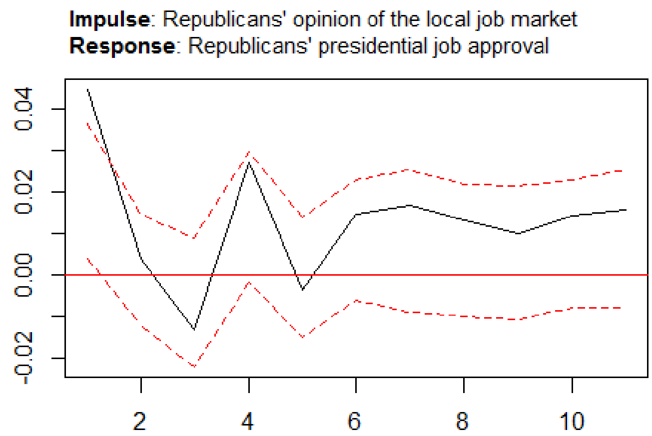


However, it was anti-trade and anti-China frames that appeared to influence public opinion about local job availability and the President. In particular, anti-trade and anti-China frames decreased Republican's public opinion about the president or the job market. The same was not true of Democrats as, in the model, only Democrats' perception about the way the President handled the economy was shaped by pro-trade discourse—this relationship also disappeared in the Impulse Response Function. For all other IRFs involving shocks to public opinion, see Figure 12.

Figure 12. IRFs of Relationships in Wisconsin







While a few of the relationships disappeared, the impulse response functions confirmed many others:

(1) anti-trade frames in state newspapers decreased Republican's perceptions of the local job market after a lag of five,

(2) anti-China frames decreased Republican's perception of the local job market (though the effect of national television is very small) and how the President was handling the economy at a lag of two,

(3) anti-trade frames in national media decreased Republican's perception of the President at a lag of two, and

(4) Republicans' opinion of the local job market increased Republicans' presidential job approval at a lag of one.

Summary. These results provide evidence that both news media and the China shock experienced by Wisconsin both help to explain Republican's perceptions of the local economy and of the President. Public opinion among Democrats, on the other hand, were not particularly responsive to either economic or media variables.

These results suggest that manufacturing jobs alone do not explain Republican's perceptions of their local job market or of the President—news media appears to have a notable influence as well. While increases in of manufacturing jobs was related to more pro-trade articles in state newspapers, it was negative frames (anti-trade and anti-China frames) that decreased people's perceptions of the local job market and President. In Wisconsin, I did not find relationships between news media and Democrats' public opinion.

This case suggests that, at the state-level, Wisconsin news media did publish positive trade stories when manufacturing employment increased. However, it was the negative national and state-level newspapers that decreased people's perception of the local job market and the President. Importantly, an increase in manufacturing jobs also Granger caused an increase in Republicans' perception of the local job market. Therefore, both news media and state-level economic factors shaped public opinion.

Florida: Worrying about a China Shock that Didn't Happen

Florida has the fourth-largest economy in the country, hitting a $1 trillion milestone in 2018 (Lynch, 2018). Though Florida's economy is fairly diverse, it is buoyed by two key industries: tourism and agriculture. Of the 9.1 million people employed in Florida, about 14% (1.3 million) have jobs related to the tourism industry; Walt Disney World is by far the largest employer in this sector (Walton, 2019). Agriculturally, Florida's main exports include greenhouse and nursery products, including landscaping plants, and citrus.

Manufacturing in Florida is a relatively small percentage of its total employment or output. Over 12,000 firms employ 382,000 employees, less than 5% of the state's nonfarm employment (National Association of Manufacturers, 2020). Though Floridian manufacturing firms employs more workers than Wisconsin, its combined manufacturing output is smaller in both raw value, $55.89 billion, and in percentage of the gross state product, 5.39%. A substantial portion of the manufacturing output is centered around aviation equipment, due in no small part to the aviation and aerospace industry already in Florida (Roberts, n.d.).

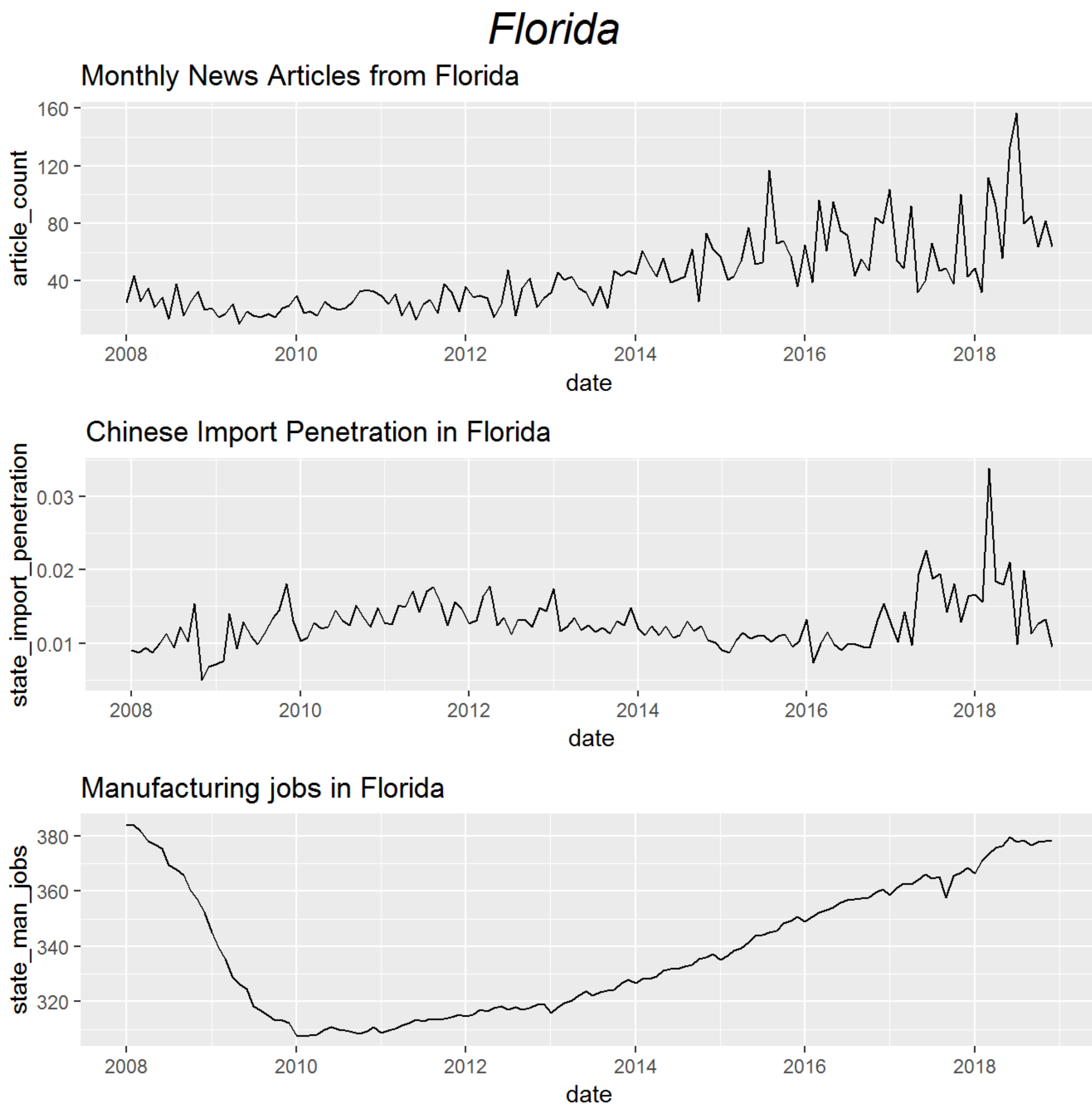
Unlike Wisconsin, most studies agree that Florida was not particularly impacted by a China shock. Although Florida was among the states with the most jobs displaced by the U.S.-China trade deficit, it was a small proportion of the state's overall employment (Scott & Mokhiber, 2020).

Politically, Florida has had a Republican Governor since 1999. Rick Scott [R] was the Governor of Florida for the majority of the time frame (he was term-limited in 2019). Nevertheless, Florida is still considered a swing state (Foreman, 2018), particularly because so many of its recent elections have been won by very tight margins: in 2016, Trump won by a 1.2% margin; in 2012, Obama won by a margin of 0.9%.

Figure 13 displays the number of articles published by Florida newspapers about U.S.-China trade, the import penetration ratio for Wisconsin, and the number of manufacturing jobs. Like Wisconsin, news coverage of U.S.-China trade rises from 2015 to 2017 and has the two notable spikes in January and March attributable to President Trump's tariffs.[63] Unlike Wisconsin, anti-China frames were the most common in Florida newspapers (n = 2,021), followed by pro-trade frames (n = 983) and anti-trade news stories (n = 323).

[63] In the state newspaper corpus, Florida is represented by 10 outlets: Florida Times-Union (owned by Gannett), Florida Today (owned by Gannett), Naples Daily News (owned by Gannett), Pensacola News Journal (owned by Gannett), Tallahassee Democrat (owned by Gannett), The News-Press (owned by Gannett), Tampa Bay Times (owned by Times Publishing Company), The Tampa Tribune (owned by Revolution Capital Group), Sun-Sentinel (owned by Tribune Publishing) and Orlando Sentinel (owned by Tribune Publishing). They published 3,180 stories.

Figure 13. Florida News Media, Import Penetration, and Manufacturing Employment



In Florida, import penetration spikes at the start of 2018; this aligns with other research showing that total imports from China to Florida in 2018 exceeded that of 2017 and 2019 (Enterprise Florida, n.d.). One explanation for this spike may be a pre-emptive stockpiling of Chinese goods before the tariffs took effect (this also occurred under the Bush administration, see Glader, 2004) Although there is a notable drop in manufacturing employment from 2008 to 2010, import penetration is relatively small until the end of the time span, suggesting that the 2008-2010 job loss is likely related to the 2008 recession, and not a China shock.

VAR(3) Model. To construct a VAR model to analyze Florida, I follow the same procedure used to prepare the data for the other time series analysis: identify time series that are non-stationary, first-difference non-stationary time series, and detrend seasonal components in the import penetration time series. In addition to the 17 variables typically included in the model, I added one control: the monthly unemployment rate in Florida, to control for the overall labor market and not just the manufacturing sector. In the Florida data, 12 variables were non-stationary.

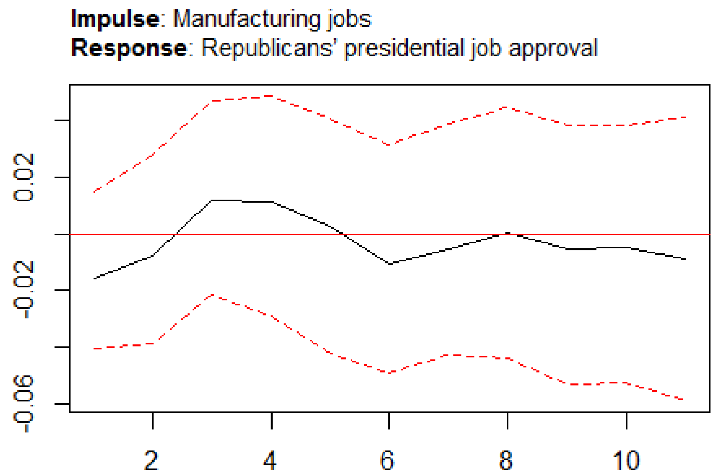
Using the AIC, I determined that the optimal model had a lag of 3 (AIC = -3.732). Once I constructed the VAR(3) model, I ran Granger causality tests between the variables. Table 12 displays the statistically significant results.

Table 12. Statistically Significant Granger Causality Tests for Florida, VAR(3)

Relationship	x^2	p-value
National NP, Pro-Trade Frame → Local Job Opinion, Dem.	12.70	0.013
National TV, Pro-Trade Frame → Local Job Opinion, Dem.	12.82	0.012
National TV, Anti-Trade Frame → Local Job Opinion, Dem.	10.51	0.032
National TV, Anti-Trade Frame → Pres Handling the Economy, Dem.	11.61	0.020
National NP, Anti-China Frame → Presidential Job Approval, Dem.	12.48	0.028
National NP, Anti-Trade Frame → Local Job Opinion, Rep.	15.44	0.004
National NP, Anti-China Frame → Local Job Opinion, Rep.	12.89	0.009
National NP, Anti-China Frame → Pres Handling the Economy, Rep.	16.01	0.002
Manufacturing Jobs → Presidential Job Approval, Rep.	13.49	0.009
Local Job Opinion, Rep. → Presidential Job Approval, Rep.	11.26	0.024

Importantly, I do not find evidence of a China shock, as import penetration did not Granger cause manufacturing jobs. The number of manufacturing jobs did Granger cause Republican's Presidential job approval ($X^2 = 2.81$, $p < 0.01$). However, this relationship disappears once controlling for all other variables in the Impulse Response Function (see Figure 14).[64]

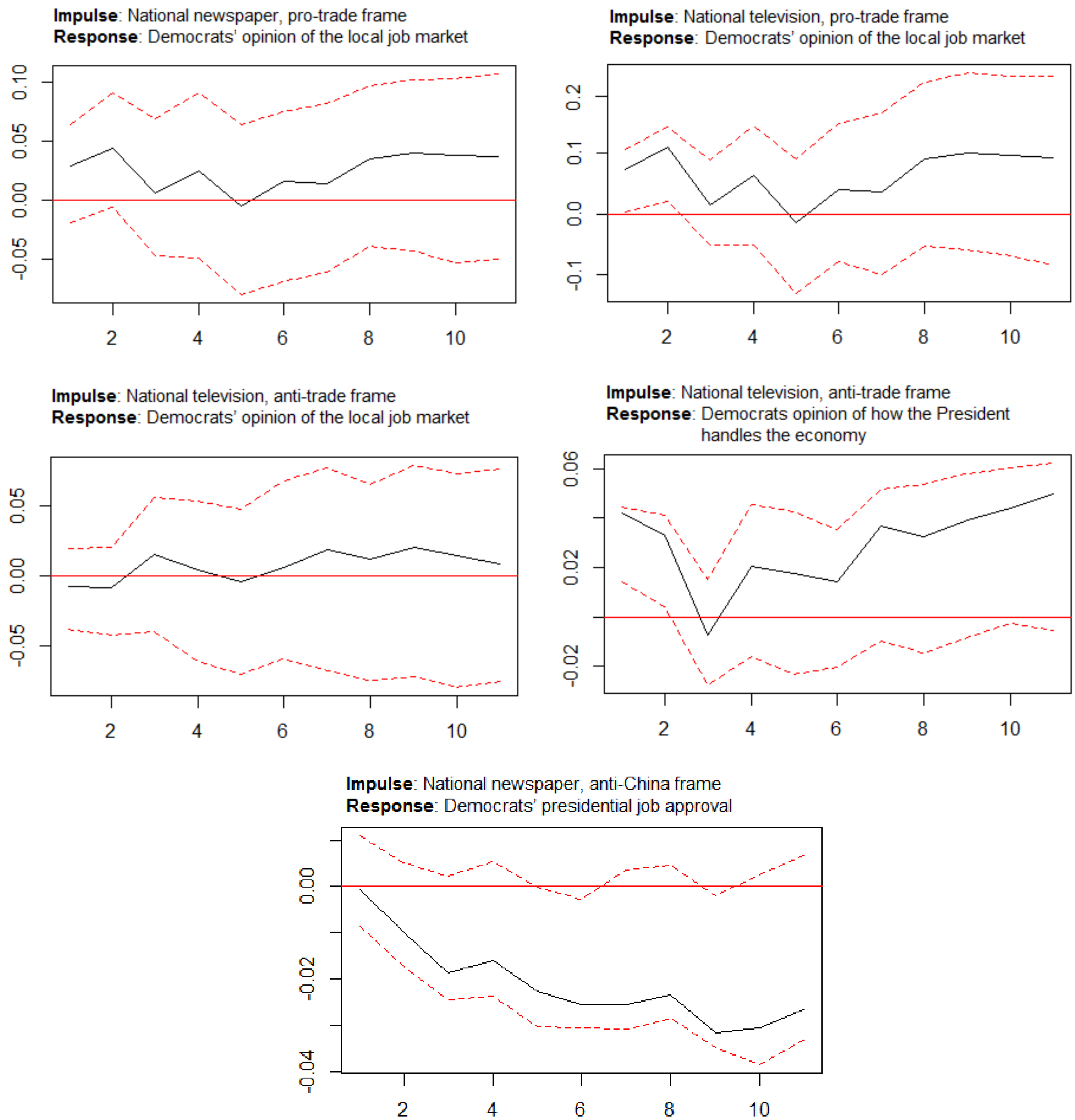
Figure 14: Impulse Response Function of Manufacturing jobs on Republican Opinion of the Local Job Market, FL

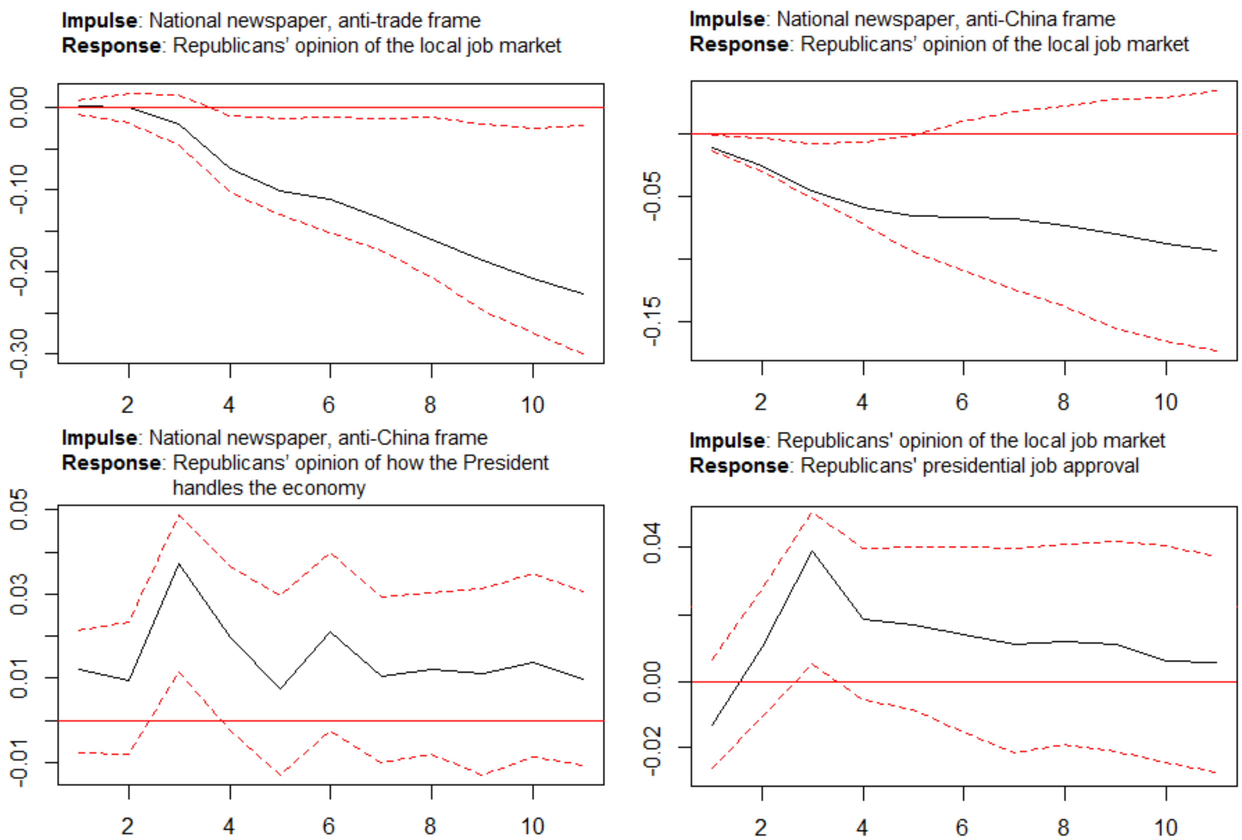


Frames in national newspapers and television did Granger cause people's public opinion about the economy and the President. Frames in national newspapers were related to Democrats' and Republicans' perceptions of the local job market. Some of these relationships were confirmed with impulse response functions (see Figure 15): pro-trade frames in television programs increased Democrats' attitude of the local job market and anti-trade frames in television programs increased Democrats' opinion of how the President was handling the economy. But anti-China frames in television programs decreased support for the President.

[64] The unemployment rate did not Granger cause opinions about the local job market for Democrats ($x^2 = 1.25$, $p = 0.279$) or Republicans ($x^2 = 0.96$, $p = 0.461$).

Figure 15. IRFs of Relationships in Florida





Republicans in Florida were more greatly impacted by national newspapers. National newspaper articles with anti-China frames seemed to decrease perceptions of local jobs earlier, between lag 2 and 4, than anti-trade frames in news articles, which occurred at lag 4. Anti-China news stories in newspapers article increased people's approval of the way the President handles the economy. These results suggest that, even in a state that is not suffering substantially from the China shock, news media can still shape people's perceptions of the local job market and the President, even when controlling for state-level unemployment. This is a curious result, as it suggests that national news media can induce concern about the local labor market without an actual local trade shock occurring. National television framing influenced Democrats' public opinion more, while national newspapers decreased Republicans' perceptions of the local job market.

These results speak to a troubling pattern recently identified in academic scholarship: as politics and news coverage becomes increasingly more nationalized, people lose their ability to make sense of what is happening in local or state politics (Hopkins, 2018) or, in this case, state economic condition. This is not misinformation per se, but because media coverage focuses on the national economy, people's perception of the state economy becomes distorted, resulting in an incorrect perception of the local labor market. Such findings highlight an ongoing problem with economic news presented to the general public: people's political attitudes may be shaped by a misunderstanding about the state economy because the news information available about the economy is nationally-focused.

New Hampshire: A Northeastern State Reliant on Manufacturing

Tucked deep in New England (the birthplace of American manufacturing in the 1800's), New Hampshire's economy has historically relied on a variety of manufacturing industries, from textiles to finished clothing products (Bookman, 2017). In recent years, manufacturing has become a smaller portion of both the state's output and employment in the state. In 2002, retail trade overtook manufacturing as the industry with the highest employment in New Hampshire (U.S. Bureau of Labor Statistics, 2016). By 2018, New Hampshire was employing 70,000 employees in manufacturing jobs, constituting a 10.34% share of non-farm employment. New Hampshire produces nearly $10 million in manufacturing output, which was 11.63% of the gross state product (National Association of Manufacturers, 2020).

New Hampshire became a swing state in 1992 (Koczela, 2016). Though New Hampshire is influenced by progressive moments in the broader New England era, the state also has a libertarian streak, as emplified by their state motto: "live free or die" (Nagy, 2001). At the start of the time frame, the Governor if New Hampshire was John Lynch [D], who was succeeded by

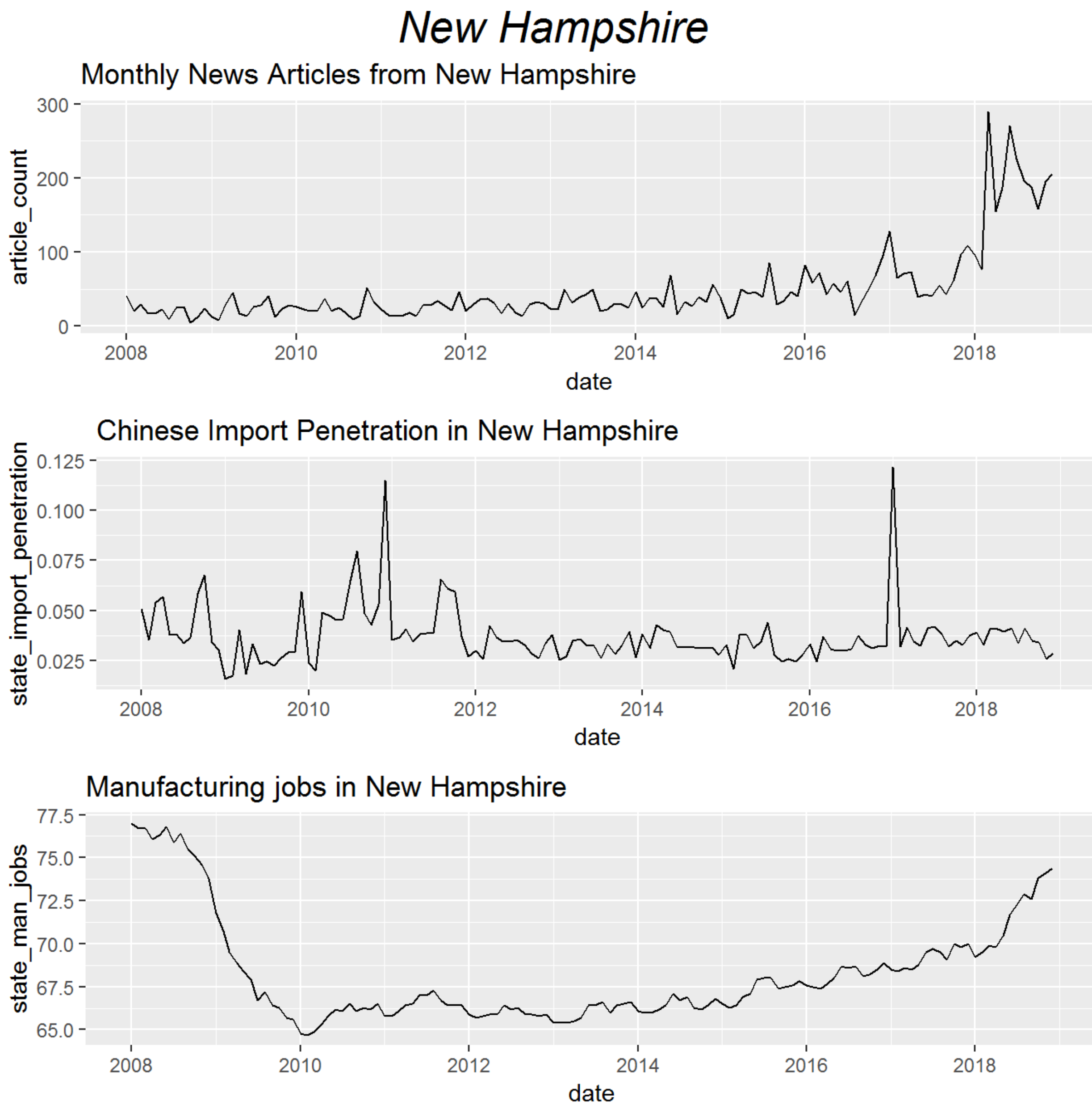
Maggie Hassan [D] in 2013. The 2016 election saw many close elections in New Hampshire. Hassan was elected to Senate, narrowly defeating incumbent Kelly Ayotte [R] (with a 0.2% margin). in 2016. Chris Sununu [R] won the Governorship to replace Hassan, beating Democratic candidate Colin Van Ostern with a 2.2% margin. Clinton won the state, barely, with a margin of 0.4%.

Figure 16 displays the number of articles published by New Hampshire newspapers about U.S.-China trade, the import penetration ratio for New Hampshire, and the number of manufacturing jobs in New Hampshire.

New Hampshire's news spike is especially prominent, with more stories in January compared to March.[65] The majority of the articles used anti-China frames (n = 1,808), followed by pro-trade frames (n = 445) and anti-trade stories (n = 276). Relative the other state cases, manufacturing employment growth post-recession appears to be slower.

[65] In the state newspaper corpus, New Hampshire is represented by six outlets: Carriage Town News (independent ownership), Foster's Daily Democrat (purchased by Gatehouse in 2016, which later went on to purchase and become Gannett in 2019), The Boston Globe (although this newspaper is based in Massachusetts, its market extends to New Hampshire), The Telegraph (owned by Ogden Newspapers), New Hampshire Sunday News (owned by Union-Leader Corporation), and The Union Leader (independently owned by the Union-Leader Corporation). They collectively published 3,187 articles.

Figure 16. New Hampshire News Media, Import Penetration, and Manufacturing Employment



VAR(2) Model. To construct a VAR model to analyze New Hampshire, I follow the same procedure used to prepare the data for a time series analysis: identify time series that are non-stationary, first-difference non-stationary time series, and detrend seasonal components in the import penetration time series. In the New Hampshire data, 13 variables were non-stationary. There was no seasonal component in the import penetration variable.

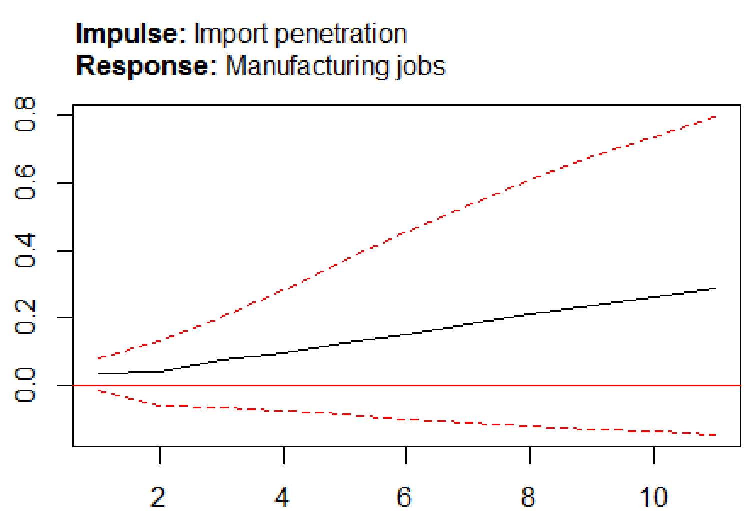
Using the AIC (-3.271), I determined that the optimal model had a lag of 4. Once I constructed the VAR(2) model, I ran Granger causality tests between the variables. Table 12 displays the statistically significant results.

Table 13. Statistically Significant Granger Causality Tests for New Hampshire, VAR(2)

Relationship	X^2	**p-value**
Import Penetration → Manufacturing Jobs	14.46	0.005
Manufacturing Jobs → Local Job Opinion, Dem.	8.18	0.042
Pres Handling the Economy, Dem.→ Presidential Job Approval, Dem.	12.85	0.005
National TV, Pro-Trade → Local Job Opinion, Rep.	25.67	0.000
Pres Handling the Economy, Rep.→ Presidential Job Approval, Rep.	17.62	0.001

Though there was evidence of a China shock in the Granger causality tests, this relationship disappeared once controlling for multiple variables across multiple lags (see Figure 17).

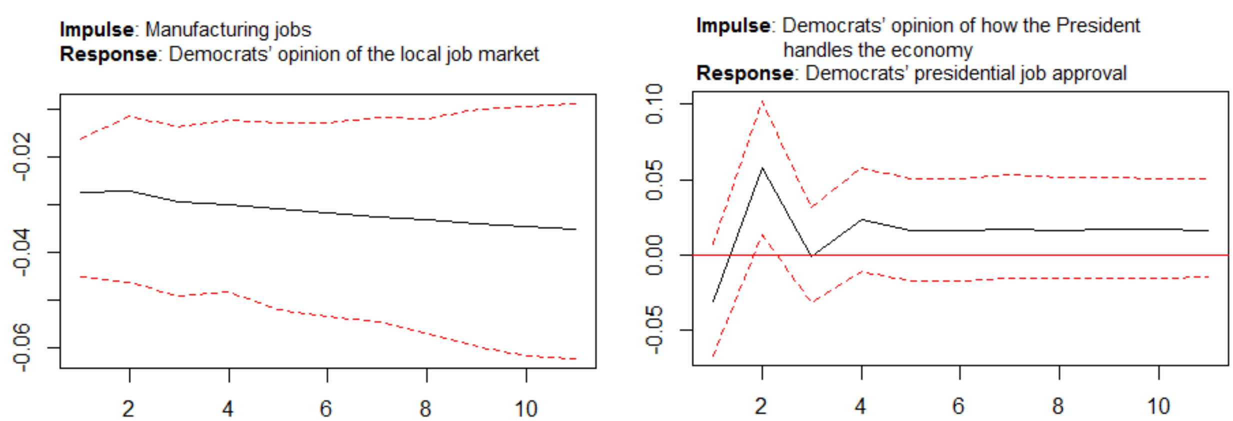
Figure 17. Impulse Response Function of Import Penetration on Manufacturing Jobs, New Hampshire

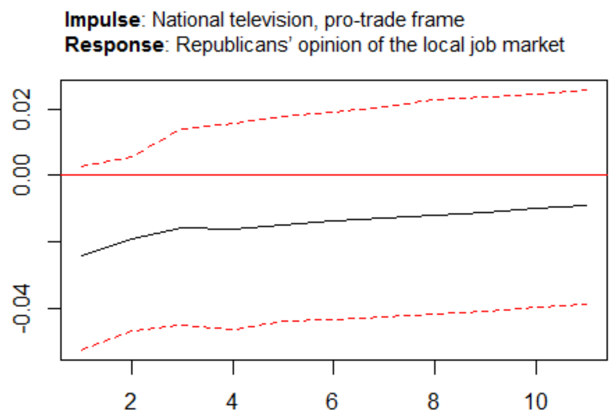


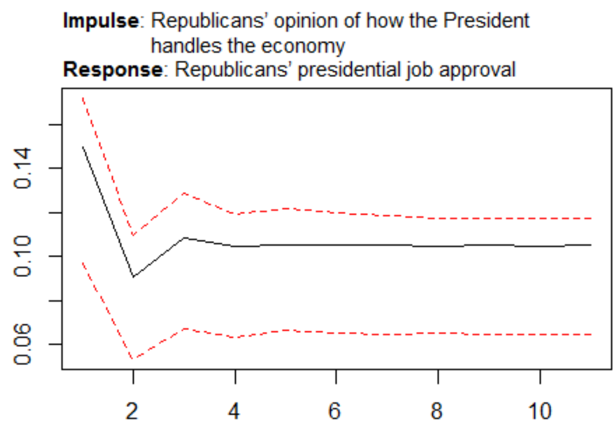
Why is this the case? One explanation may be the specific sector New Hampshire calls "smart manufacturing/high technology," which includes all their manufacturing companies and high-tech companies; it is the largest manufacturing sector in New Hampshire in contribution to GSP (New Hampshire Center for Public Policy Studies, 2011). Smart manufacturing, in particular, refers to the use of automated operations and data analytics to monitor manufacturing, decreasing the number of people necessary to operate a machine. As a result of smart manufacturing, automation may be contributing to manufacturing job loss more import penetration from China.

Turning now to news: only national news programs with pro-trade frames Granger caused perceptions of local media, but this relationship disappeared in the impulse response function. Interestingly, there was also a separation between state/local and national variables: manufacturing jobs Granger caused perceptions of local jobs in the area for both Democrats and Republicans and perceptions about how the President handled the economy Granger caused perceptions of how the President was handling his job, but local manufacturing jobs and perceptions about local job market did not Granger cause national-level public opinion variables.

Figure 18. IRFs of Relationships in New Hampshire







Discussion

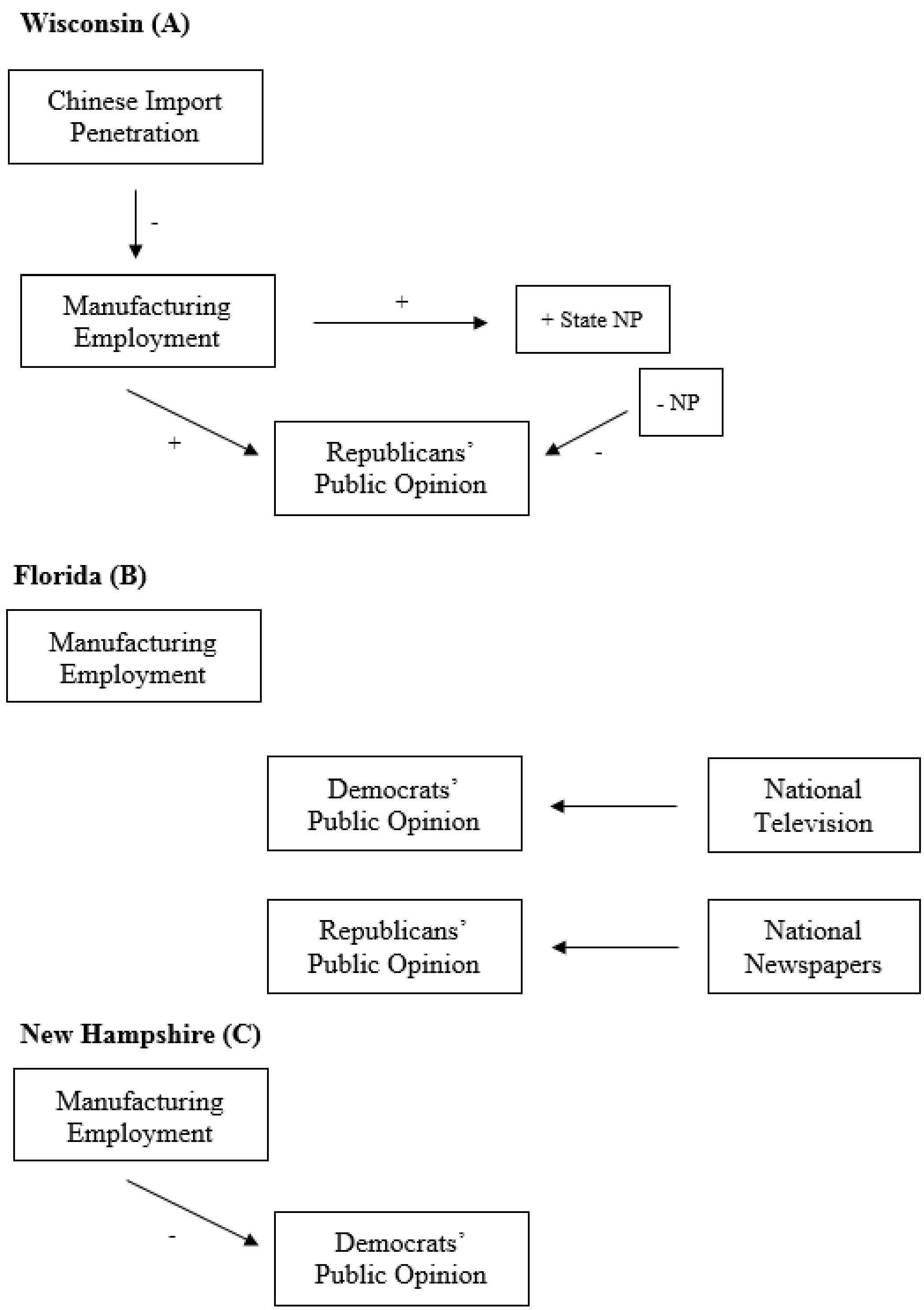
The results of these cases highlight the substantial variation of economic and news influences between states. As Wisconsin's economy relies on is diverse manufacturing sector, I found a statistically significant and negative relationship between Chinese import penetration and manufacturing employment. Manufacturing employment Granger caused both Republicans' perceptions of the local job market and state-level news coverage framing trade with anti-China language. In turn, state newspapers Granger caused lower perceptions of the local job market and the way the President was handling the economy. Impulse response functions suggested these relationships occurred between a lag of one and four.

Unlike Wisconsin, Florida's economy is less reliant on manufacturing. Though specialized manufacturing sectors (e.g., aviation manufacturing) are important to the state economy, the agriculture and tourism industries in the state make up a much greater part of Florida's GSP and unemployment. Correspondingly, I find no evidence of a China shock. However, I did find several relationships between national news media and people's perceptions of the local job market and of the President. These relationships were different for Democrats and Republicans: Democrats' perception of the local economy and the President increased with national pro- and anti-trade television news programs. Republicans, on the other hand, had a decreased perspective of the local job market when there were more national newspaper articles framing U.S.-China trade negatively, using an anti-trade or anti-China perspective. Curiously, the effect of anti-China news stories began earlier compared to anti-trade news stories. Republicans' perception of how the President was handling the economy was also higher when there were more anti-China newspaper articles. Taken together, we find a curious influence of national news media on public opinion (even when controlling for the state's overall unemployment rate), but not state-level news as we saw in Wisconsin.

In New Hampshire, another state with a strong manufacturing sector, manufacturing job loss didn't seem attributable to import penetration from China. However, manufacturing jobs did Granger cause Democrats' and Republicans' perception of the local job market. One explanation for this is may be that people in New Hampshire are attentive to manufacturing job loss as a result of automation, rather than a China shock. Manufacturing employment and import penetration did not influence news coverage, and news coverage did not influence New Hampshire Democrats' or Republicans' perception of local employment or the President. New Hampshire, in particular, highlights the importance of regional economies when thinking about the China shock, as manufacturing job lost cannot be attributable solely to Chines import penetration.

Using the model proposed in Chapter 2, I illustrate the statistically significant relationships identified in the Wisconsin, Florida, and New Hampshire VARs in Figure 18.

Figure 18. Relationship Between Economic Trends, News Media, and Public Opinion in Wisconsin (A), Florida (B), and New Hampshire (C)



Taken together, these results emphasize the importance of geographic variation when studying (1) whether a China shock occurred, (2) whether people's public opinion is informed by economic trends, and (3) news and the economy's combined influence on public opinion. It is important to remember that the time frame studied in this dissertation is *after* the peak of the China shock (which occurred prior to the 2008 recession). Of the state cases I studied, only the Wisconsin model had evidence of the China shock.[66] One major reason why Wisconsin may still suffer from a China shock is the diversity of manufacturing industries in that state: relative to other states, Wisconsin is likely to have manufacturing sectors still suffering from the China shock (Sester, 2018), even when some manufacturing sectors have recovered.

In states where manufacturing makes up a large part of their GSP or employment, people may be more attentive to manufacturing employment because it forms the foundation of their economy. This was noticeable in the New Hampshire and Wisconsin cases. In Wisconsin, Republicans' opinions of the local job market increased when manufacturing employment increased. But in New Hampshire, Democrats' opinions of the local job market decreased as manufacturing employment increased. One explanation for this difference may be the party's interpretation of manufacturing: Republicans perceive private manufacturing employment as a key driver of job creation, while Democrats advocate for more public infrastructure programs (Newport, 2011). In New Hampshire, both Democrats and Republicans advocate for smart manufacturing, which includes automation to increase manufacturing output.[67] In that state, therefore, having more manufacturing employment may not be perceived in the same way.

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[66] I also ran VAR models for Pennsylvania and Michigan; neither had evidence of a China shock from 2008 to 2018.
[67] New Hampshire Senator Jeanne Shaheen [D], for example, introduced a "Smart Manufacturing Leadership Act," which would make grants available for manufacturing companies to invest in smart manufacturing to improve "productivity and energy efficiency." The bill encourages the use of automation to increase output and energy efficiency.

However, states that are not particularly reliant on manufacturing could still be primed by national news media to pay attention to manufacturing job loss, especially from national news media and especially when the coverage is negative (e.g., anti-China or anti-trade framed communication). In Wisconsin, national news media stories framing U.S.-China trade with anti-trade or anti-China sentiments was related to decreased public perceptions of the local job market and how the President was handling the economy. In Florida, anti-China and anti-trade framing decreased public opinion of the local job market but was related to an increased perception of how the President was handling the economy, perhaps because this coverage justified foreign economic policy action against China. The public's use of national information to shape their understanding of the local economy is made worse because a substantial amount of local news reporting (which was influential to Wisconsin Republicans' public opinion) is nationally-focused. Therefore, even if people read local news to understand their local economy, they are still likely consuming information about national trends.

This provides evidence that sociotropic factors may be more influential when a geographic region is more greatly impacted by a trade shock or national news media frame trade negatively. The evidence of a geographically-varied China shock aligns with previous research on the China shock (e.g., Autor et al., 2016) and suggests that fewer states are suffering from the China shock relative to the 1990-2007 era. In states where manufacturing comprises a large portion of the economy, citizens' political attitudes may be shaped by regional sociotropic factors: manufacturing employment in the state probably matter more than manufacturing employment nationally.

However, because it is national news media that influences public opinion, people may use national economic trends to understand their local economy. This is particularly evident in states where manufacturing is not a core part of the state's economy, like in Florida: in this state, national news media framing U.S.-China trade with anti-trade and anti-China sentiments appeared to shape people's perception of the local economy *and* the President (even when controlling for overall employment). This suggests that people may not be as attentive to local economic trends as scholars hoped they would be.

Chapter 8: Discussion

Even if the overall effects of open trade with China is beneficial to the United States, as recent economic scholarship would suggest (Caliendo, Dvorkin, & Parro, 2019), the (short-term) job loss in the manufacturing sector have substantive political consequences that cannot be ignored. It is essential that researchers study how people make sense of trade, especially given that globalization is unlikely to stop.

In this dissertation, I argue that news plays an essential role in this sense-making process. When reporting on trade, journalists must go beyond just objectively providing information to help citizens understand the consequences of global economic trends as they relate to perceptions of their local economy. In this way, how journalists report on trade is similar to coverage of other economic issues (Soroka et al., 2015). News framing is a helpful process for contextualizing stories about trade because, through frames, journalists are able to emphasize information that help people relate information to their lifeworld.

To study the relationship between news frames, economic trends, and public opinion, I began with a frame analysis of local and national news coverage of U.S.-China trade over the past decade, accounting for both print and television news coverage. The results, described in Chapter 5, highlight a skew towards stories criticizing U.S.-China trade, particularly framing China as a bad faith actor. The results also show that local news media’s coverage of U.S.-China trade was often nationally focused.

I then performed a set of time series analysis, first looking at national trends and then focusing more closely on state-level variation. To illustrate the differences between states, I explored three state-cases, Wisconsin, Florida, and New Hampshire, to show how regional economic variations shape both news coverage and the combined influence of news and the economy on people’s perceptions of the local job market and of the President. Below, I describe my major findings.

Major Findings

There is more negative coverage about U.S.-China trade than positive coverage.

Results of the content analysis suggest that U.S. news media framed trade with China negatively, emphasizing either anti-trade arguments or anti-China arguments. Importantly, this is not negative in just the use of sentiment language, but sentiment as related to perceptions of open U.S.-China trade; stories using positive language about tariffs would be considered a story framing U.S.-China trade negatively. The presence of both anti-trade and anti-China story frames highlights the public understanding that trade is an issue related both to international status and material (“pocketbook”) considerations.

Of the two negative story frames, anti-China framing—covering trade in relation to intellectual property theft, currency manipulation, unfair trade restrictions, and the cheap quality of Chinese goods—was more common than anti-trade framing—covering trade in relation to job loss and import penetration or advocating for protectionist policies. As a result, many news media stories framed U.S.-China trade imbalances as less about a trade shock and more about fairness; ‘it’s not that trade is bad, but that China is an unfair partner.’ The use of a non-economic explanation or heuristic for an economic phenomenon is common in economic reporting to make a story more accessible to the general public (Rugeley & Soroka, 2014), however, this may result in an inaccurate interpretation of the economic realities. For example, there were news articles framing China as a currency manipulator throughout the timespan of the study, but China was no longer a currency manipulator by 2014 (Bergsten, 2016).

A fallacy of division: Using national news to interpret the local economy

The results of the framing analysis also showed that local news articles about U.S.-China trade were more likely to mention the United States or the President than they were to mention the Governor, a city, or a county in that state. Therefore, even if someone read a local newspaper about U.S.-China trade to make sense of their economy, many of the stories would focus on national-level economic trends. To some extent, this makes sense: after all, it is the President that primarily determines trade policy. However, as the effects of the China shock varied by geography, news coverage focusing on national economic trends likely obfuscated important state and local-level differences in the China shock effect that are relevant to citizens in different states or geographic areas.

In addition to this finding, the time series models indicated that people's public opinion was more related to national news media than to state-level newspapers. Importantly, the relationship between news media and public opinion even existed in states that did not experience a China shock during the study's time frame (2008-2018). For example, in the Florida case, national newspapers and television shaped public opinion about both the local job market and the President. I therefore find evidence that news media and the public's attention to U.S. politics is becoming increasingly nationalized (Hopkins, 2018).

These two results suggest that public opinion may be more greatly shaped by news coverage of national trends, rather than local ones, about U.S.-China trade. Given that the effects of the China shock varied geographically, news media's focus on the national economy produces a fallacy of division, wherein someone assumes what is true of the whole is also true of its parts.[68] In the findings of this dissertation, U.S. citizens appear to be using information about national economic trends (either from national news itself or from local news covering national trends) to make sense of the local job market. This fallacy can have important political consequences, as the time series analyses also indicated that people's perceptions of their local job market were related to how they evaluated the President in several states (i.e., Florida and Wisconsin). The possibility of a fallacy of division related to misapplied national information should be of great concern to social scientists as a source of economic misunderstanding.

News media and the China shock influences on public opinion vary by state.

The geographic variation of the China shock likely contributed to differences regarding the influence of news framing. My cases show that news media can shape people's opinions about their local job market and the President (e.g., Wisconsin and Florida), but it does not always happen (e.g., New Hampshire). One explanation for this may be that manufacturing states are particularly attentive to the specific regional factors influencing manufacturing job loss (in the case of New Hampshire, smart manufacturing is a more viable culprit). This also emphasizes the value of accounting for state-level variation when studying trade preferences and raises the possibility of local sociotropic trade preferences, somewhere in between self-interest and national sociotropic influences (Alkon, 2017).

In one case (Florida), I found that news media framing of U.S.-China trade did influence Floridians' attitudes about their local job market and the President, even when controlling for both manufacturing employment and the state unemployment rate (Florida's primary industries are tourism and agriculture, though it has a notable aviation manufacturing sector). This may hint

[68] This is considered an informal fallacy. The formal equivalent is an ecological fallacy (when statistical information about the group is used to make an incorrect inference about a part of the group). The Simpson's paradox is considered a special type of ecological fallacy.

at a more national sociotropic phenomenon: in states where the China shock was not substantial, people's political attitudes may still be shaped by national news stories about U.S.-China trade.

A brief note on misinformation. Though I did not set out to study misinformation when I began this dissertation, it is important to acknowledge how some of the processes identified in my dissertation can unintentionally mislead people about trade. First and foremost, the focus on national news trends may produce a fallacy of division, misleading people's understanding of their local economy (e.g., people may think a China shock is happening in their local economy when it is not). Second, some frames rationalizing the use of protectionist policies could constitute misinformation. For example, there is general consensus that China was no longer a currency manipulator (Bergsten, 2016); however, framing China as a currency manipulator persisted into 2018. While President Trump likely contributed to this trend, there were very few stories that corrected his assertion. This highlights the possibility that framing can unintentionally distort chronological details about economic trends.[69] While this information may be accurate in a certain geographic or temporal context, the way in which the public uses this news information to evaluate the local economy and the President may constitute some form of misinformation; or, at minimum, a misapplication of national sociotropic information.

Summary

Understanding these findings holistically, I identify two factors that could contribute to sociotropic economic attitudes: geography and nationally-focused, negatively-framed news media coverage of U.S.-China trade. The former suggests that geographic variations of the China Shock produced state-level sociotropic attitudes (Alkon, 2017). The latter highlights the

[69] This is setting aside some of the more overt forms of misinformation. For example, the President himself has made the inaccurate claim that tariffs are paid for by China (Timm, 2019). Thankfully, my corpus suggests that (with the exception of a few Fox programs), news media tended to correct this misinformation.

influence of negative news stories (Guisinger, 2017; Soroka, 2006) and illustrates how people's understanding of their local economy and the President may be shaped by national economic information.

Statistically, the differences between the national model and the state-level model suggest a Simpson's paradox, wherein a relationship identified between two variables across multiple groups disappears when the groups are aggregated. In the national VAR, it appeared as if the China shock and news coverage about U.S.-China trade were not related to people's political or economic public opinion. However, the multi-level VAR and the case analyses highlight geographic differences in both the China shock and the influence of news coverage about U.S.-China trade. This statistical phenomenon, in turn, produces a fallacy of division in public opinion: because we consume news information about national trends (and primarily news stories criticizing U.S.-China trade), our understanding of U.S.-China trade may not accurately reflect our local economy.

While my dissertation focuses specifically on economic information, it is possible that this phenomenon is evident in other news information. For example, in health communication, focusing on national trends would obscure hotspots during a pandemic (such as COVID-19). People who use national information about a pandemic to understand their local circumstances may therefore be unwittingly engaging in a similar fallacy of division.

People deserve to know how the economy works: A public scholar's responsibility

One point of frustration that has plagued me while working on this dissertation has been the way in which academics have disparaged everyday citizens and journalists for mis-interpreting or mis-understanding economics (e.g., Facchini, 2017). If the general public does not understand "the economy," perhaps it is because we scholars have failed to explain it well enough. A person should not need a Ph.D to know how the global economy will influence their economic lifeworld. As the world becomes increasingly globalized, it is essential for citizens to understand glocal economic trends in their lifeworld. International trade news can no longer be relegated to the financial sector where it will be read primarily by stockbrokers and financiers (Gans, 2014)—it must be contextualized and explained to the general public because globalization impacts everyone.

With this in mind, I argue that it is essential for academics, researchers, and scholars to work with journalists to report on news about trade to the public. This is especially important at the local-level, where journalists generally have fewer resources to cover the economy comprehensively for their audience. Such a relationship should go beyond simply being quoted in a news story about trade—after all, collaborative endeavors to study local-level trade effects can be beneficial to the journalist, the academic, and the local community at large.

Limitations and Future Directions

It is not possible for one project to fully capture the dynamics that influence people's perception of trade and the economy. While my dissertation highlights several key considerations—in particular, news media framing and regional variation—that could relate to public opinion and trade, these findings should be elaborated upon with additional research.

In this dissertation, I chose to work with aggregate-level information because individual-level data obscures sociotropic political attitudes (Kramer, 1983). Furthermore, it is difficult to account for long-term economic trends in a cross-sectional experiment or survey. However, limitations of this strategy include having less control over the public opinion questions I could study (to my knowledge, no survey consistently asks similar questions about trade over the course of ten years) and not being able to account for individual-level factors such as education, which has a known relationship with trade preferences (Mansfield & Mutz, 2009).

My analysis also narrowly focuses on legacy news media; specifically, print and television news coverage of U.S.-China trade. In the hybrid media system, there are many more media actors involved, including digital outlets and hyper-partisan media. I focused on print and television specifically for several reasons. First, traditional news media continue to play an essential role in reporting on foreign policy and economic issues (Aday, 2017; Damstra, Boukes, & Vliegenthart, 2018). This is especially true for economic news, as economic journalists tend to rely on traditional sources, rather than new media like Twitter (Johnson et al., 2018). Second, I wanted to emphasize the importance of genre variation when studying framed news messages—each additional news layer would require its own frame analysis to construct a register-specific lexico-syntactic dictionary. Finally, I was interested in exploring state-level variation in this study, and digital news platforms tend to be nationally-oriented.

That being said, a cross-media framing analysis of U.S.-China news coverage would be a fruitful and interesting future study. Based on the findings of this study, it may be valuable to explore differences in how partisan media frame U.S.-China trade. If there are national sociotropic news influences, partisan media may prime individuals to align more with their party, even if their local economy suffers as a result. Another consideration is to study national news media and politicians' rhetoric, which can shape trade preferences (Boucher & Thies, 2019).

Another potential future study could focus specifically on the protectionist policies by the Trump administration. While other presidents have imposed tariffs, no modern President has levied as many tariffs (to China or other states) as President Trump has. In 2018, President Trump had begun to impose a wide range of tariffs on Chinese goods. My time frame therefore does not capture the long-term consequences of these policies, though recent studies have found that the U.S. economy—and especially the agricultural sector—was unduly harmed by retaliatory tariffs from China (Flaaen & Pierce, 2019).

Limitations notwithstanding, the findings of this dissertation highlight several key considerations for scholars seeking to understand the political consequences of trade shocks and, more broadly, social scientists studying how news media shapes public opinion at the state and national-level. Despite the fact that the China shock varied geographically (Autor et al., 2016), the increasing nationalization of politics and news appeared to result in fallacy of division wherein information about national trends was misapplied to the local economic context. These relationships do vary by state, so scholars hoping to understand this phenomenon should consider local and state-level analyses when studying how people make sense of trade and the economy. It is my hope that this study encourages people to consider both local and national factors related to how people make sense of globalization. After all, globalization still occurs within an economic system structured around individuals within nation-states—highlighting the continued mixing of the global, national, and local levels of society.

Appendix

Appendix A. List of Local Outlets

https://github.com/jlukito/dissertation/blob/master/appendixA_local_outlets.csv

Appendix B. Correlation Test of National Public Opinion Variables

		1	2	3	4	5	6	M	SD
1	Public Opinion of the Local Job Market, Dem.[1]	-						-0.08	0.31
2	Public Opinion of the Local Job Market, Rep.[2]	0.15*	-					-0.42	-0.40
3	Public Opinion of how the President is handling the Economy, Dem.[3]	0.31***	0.07	-				0.59	0.27
4	Public Opinion of how the President is handling the Economy, Rep.[3]	-0.06	0.42**	0.04	-			0.33	0.18
5	Presidential Job Approval, Dem.[3]	0.00	-0.03	0.22**	-0.24**	-		0.61	0.22
6	Presidential Job Approval, Rep. [3]	-0.02	0.13	-0.17***	0.09	-0.32**	-	0.32	0.17

[1] min = -1.18; max = 0.80
[2] min = -0.93; max = 0.63
[3] min = 0.05; max = 0.98

Appendix C. VAR

https://github.com/jlukito/dissertation/blob/master/national_VAR_model.txt

Appendix D. mlVAR

https://github.com/jlukito/dissertation/blob/master/state_mlVAR_model.txt

Appendix E. Granger Causality Test, State-Level

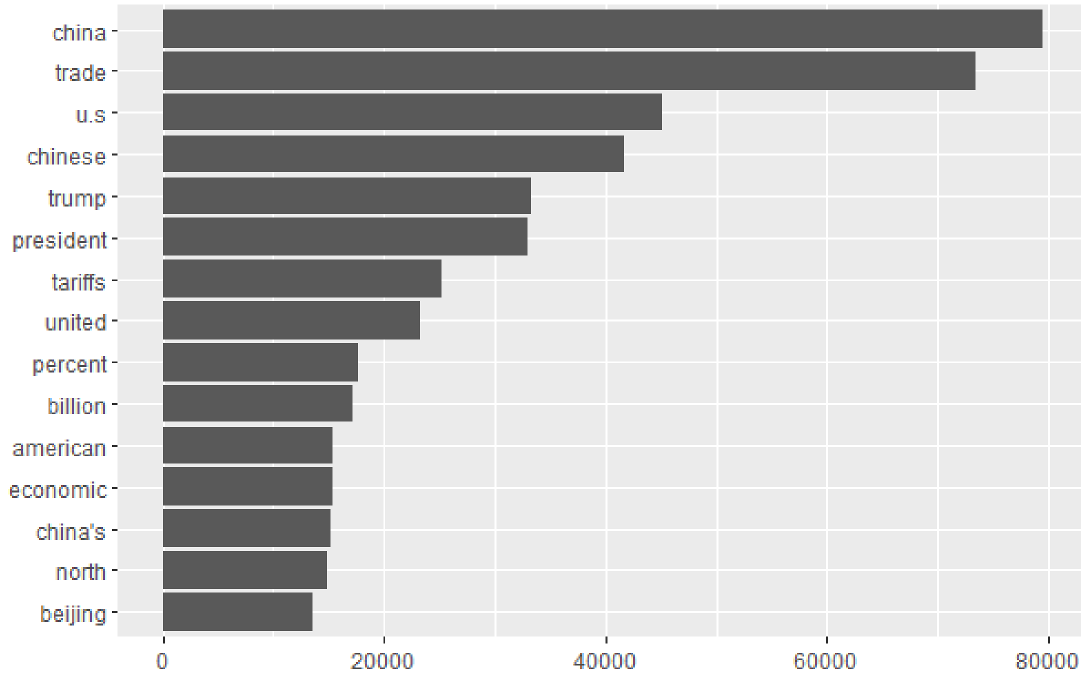
Wisconsin: https://github.com/jlukito/dissertation/blob/master/state_var_wisconsin_model.txt

Florida: https://github.com/jlukito/dissertation/blob/master/state_var_florida_model.txt

NH: https://github.com/jlukito/dissertation/blob/master/state_var_newhampshire_model.txt

Appendix F. Additional Text Analysis

[1] Top Keyword in Excerpts (Print, TV)



Note: Stopwords were removed using the tidytext() package in R (Silge & Robinson, 2020)

[2] Top Bigrams in News Stories (Print & TV)

1 White House
2 Trade War
3 Donald Trump
4 North Korea
5 Free Trade
6 Trump Administration
7 President Donald
8 South Korea
9 Trade Agreement
10 Obama Administration
11 European Union
12 Wall Street
13 International Trade
14 Vice President
15 U.S. Trade

[3] Bigram Network in News Stories (Print & TV)

[4] Structural Topic Modeling in Full News Stories (Print & TV, k = 45)

Note in these examples that television in particular produces its own unique topics. For example, topic 4 and 23 are simply Fox News programs, and topic 10, 12, 32 are CNN programs. While this also happens to some newspapers, it is less common.

Additionally, many of the topics are only tangentially related to trade. Since I am using the full articles in this analysis, it is likely that many of these articles include only a tangential reference to trade. For more on structural topic modeling, see Roberts, Stewart, and Tingley (n.d.).

Topic 1 Top Words: [N. Korea]
Highest Prob: korea, south, korean, north, kim, moon, seoul
Score: korean, korea, kim, ripley, thaad, seoul, moon
Topic 2 Top Words: [Russia Investigation]
Highest Prob: investig, russian, russia, fbi, intellig, comey, trump
Score: comey, fbi, mueller, investig, flynn, russian, nune
Topic 3 Top Words: [SCOTUS]
Highest Prob: trump, court, immigr, order, presid, execut, state
Score: immigr, gorsuch, trump, court, suprem, judg, trademark
Topic 4 Top Words: [Fox]
Highest Prob: trump, peopl, hanniti, presid, know, now, ingraham
Score: hanniti, ingraham, kurtz, trump, applaus, tonight, clip
Topic 5 Top Words: [NY Times]
Highest Prob: world, american, america, axelrod, polit, war, state
Score: axelrod, zakaria, mcdonough, democraci, nytopinion, leavitt, huntington
Topic 6 Top Words: [Fox, tax cuts]
Highest Prob: tax, cut, will, get, plan, reform, cavuto
Score: cavuto, tax, claman, deduct, gunzelman, buffett, georgia-pacif
Topic 7 Top Words: [NAFTA]
Highest Prob: mexico, canada, trade, nafta, presid, said, state
Score: nafta, mexico, canada, mexican, nieto, tariff, canadian
Topic 8 Top Words: [CNN]
Highest Prob: vaus, sesay, know, presid, think, say, well
Score: vaus, sesay, isha, jacobson, cnn, clip, oduolowu
Topic 9 Top Words: [Healthcare]
Highest Prob: republican, senat, democrat, bill, health, care, vote
Score: obamacar, senat, republican, repeal, democrat, mcconnel, medicaid
Topic 10 Top Words: [CNN]
Highest Prob: cnn, say, presid, now, video, clip, trump
Score: howel, vanier, voice-, cnn, clip, videotap, unidentifi
Topic 11 Top Words: [NFL]
Highest Prob: player, game, team, nfl, said, play, sport
Score: nfl, kilmead, lavar, donn, wnba, anthem, kaepernick
Topic 12 Top Words: [CNN]
Highest Prob: presid, say, trump, right, roman, cnn, brigg
Score: brigg, camerota, harlow, roman, cuomo, berman, kosik
Topic 13 Top Words: [EU/IR]
Highest Prob: trump, state, iran, unit, european, deal, presid

Score: iran, merkel, trump, european, macron, nato, pari
Topic 14 Top Words: [art]
Highest Prob: exhibit, art, museum, nation, work, artist, american
Score: exhibit, museum, ngagov, ave, galleri, sicr, sculptur
Topic 15 Top Words: [Fox]
Highest Prob: think, know, william, like, gutfeld, right, guilfoyl
Score: gutfeld, guilfoyl, perino, watter, boll, timpf, beckel
Topic 16 Top Words: [Protectionism]
Highest Prob: trade, protection, china, american, unit, state, countri
Score: tariff, wto, trade, trump, steel, tpp, aluminum
Topic 17 Top Words: [Food, animals]
Highest Prob: said, food, farm, farmer, year, organ, anim
Score: soybean, ivori, usda, azuz, catfish, rhino, eleph
Topic 18 Top Words: [Currency]
Highest Prob: bank, currenc, market, china, dollar, bitcoin, fund
Score: bitcoin, yuan, currenc, cryptocurr, investor, blockchain, msci
Topic 19 Top Words: [stock]
Highest Prob: compani, busi, said, billion, execut, million, invest
Score: hna, ige, leeco, ipo, alibaba, dealbook, nyt
Topic 20 Top Words: [Climate Change]
Highest Prob: compani, car, said, climat, state, will, industri
Score: emiss, solar, automak, foxconn, auto, climat, tesla
Topic 21 Top Words: [Drugs]
Highest Prob: new, drug, polic, peopl, citi, said, school
Score: opioid, fentanyl, overdos, carlson, heroin, polic, drug
Topic 22 Top Words: [South Asia]
Highest Prob: said, india, countri, govern, year, pakistan, state
Score: myanmar, modi, india, kyi, suu, nepal, najib
Topic 23 Top Words: [Fox]
Highest Prob: presid, baier, think, say, fox, trump, will
Score: baier, bret, tonight, herridg, mckelway, videotap, clip
Topic 24 Top Words: [factories]
Highest Prob: said, worker, job, work, compani, factori, year
Score: hamidu, factori, worker, hankerson, shannon, gorton, whirlpool
Topic 25 Top Words: [Moore sexual assault]
Highest Prob: moore, republican, democrat, senat, elect, say, clinton
Score: bream, moore, roy, republican, alabama, senat, sexual
Topic 26 Top Words: [North Korea]
Highest Prob: north, korea, missil, nuclear, korean, china, state
Score: korea, missil, north, korean, nuclear, pyongyang, kim
Topic 27 Top Words: [China & Hong Konh]
Highest Prob: china, chines, beij, said, parti, govern, hong
Score: hong, kong, beij, chines, china, liu, liang
Topic 28 Top Words: [PR/hurricane harvy/daca]
Highest Prob: now, hurrican, peopl, get, storm, just, will
Score: hurrican, puerto, rico, daca, irma, dreamer, harvey
Topic 29 Top Words: [possibly CNN, definitely TV]
Highest Prob: presid, think, trump, know, say, wallac, well
Score: wallac, tapper, clip, trump, hes, king, video
Topic 30 Top Words: [Oil]
Highest Prob: oil, ship, export, coal, gas, energi, price
Score: oil, lng, coal, gas, export, petroleum, barrel
Topic 31 Top Words: [hacking]
Highest Prob: compani, use, technolog, said, govern, report, secur
Score: huawei, hack, hacker, softwar, cyber, trendnet, equifax
Topic 32 Top Words: [CNN]

Highest Prob: presid, know, think, trump, cnn, right, now
Score: cabrera, whitfield, blackwel, burnett, cnn, savidg, clip

Topic 33 Top Words: [Charlottesville]
Highest Prob: presid, white, peopl, charlottesvill, say, trump, group
Score: charlottesvill, supremacist, bannon, neo-nazi, hemmer, mugab, kkk

Topic 34 Top Words: [WSJ]
Highest Prob: market, stock, investor, dow, year, compani, jone
Score: inc, dow, investor, factivia, index, reprint, emerging-market

Topic 35 Top Words: [Fox]
Highest Prob: think, right, bartiromo, presid, get, know, well
Score: gigot, bartiromo, regan, henning, trish, rollin, mcgurn

Topic 36 Top Words: [CNN]
Highest Prob: think, know, peopl, well, say, that, get
Score: maccallum, lemon, know, yes, crosstalk, clip, don

Topic 37 Top Words: [nytimes Asian briefs]
Highest Prob: new, time, york, one, brief, like, can
Score: kyota, highlighter, kentrianaki, wigmak, stypeck, wig, asiabriefing

Topic 38 Top Words: [china, tariffs, stock]
Highest Prob: china, compani, jone, dow, chines, inc, said
Score: inc, factivia, dow, reprint, jone, tariff, qualcomm

Topic 39 Top Words: [Syria]
Highest Prob: syria, attack, trump, presid, now, russia, state
Score: assad, syria, syrian, isi, bashar, palestinian, chemic

Topic 40 Top Words: [Putin]
Highest Prob: russia, putin, presid, russian, trump, meet, state
Score: putin, russia, russian, vladimir, trump, moscow, merkel

Topic 41 Top Words: [Trump Administration]
Highest Prob: trump, said, presid, hous, white, report, administr
Lift: deppisch, ---blue, --loyal, -field, -hustl, -sprawl, -talent
Score: trump, bannon, kushner, cohn, white, scaramucci, priebus

Topic 42 Top Words: [Domestic politics]
Highest Prob: presid, think, know, say, trump, hous, just
Score: blitzer, spicer, sciutto, baldwin, cnn, keilar, bolduan

Topic 43 Top Words: [Economic growth]
Highest Prob: economi, growth, percent, rate, econom, year, increas
Score: economist, growth, economi, rate, percent, debt, imf

Topic 44 Top Words: [Asian Regional Politics]
Highest Prob: trump, china, said, presid, state, japan, unit
Score: trump, abe, dutert, beij, taiwan, tsai, china

Topic 45 Top Words: [Sutherland Church Shooting; Trump/Saudi Arabia—connected by "guns"]
Highest Prob: saudi, gun, arabia, shoot, church, trump, presid
Score: saudi, arabia, church, gun, salman, sutherland, ross

[4] Structural Topic Modeling in Excerpts (Print & TV, k = 20)

I construct the STM below with just the excerpts. Although there are some non-trade stories, the focus has narrowed considerably. Topics such as Trump's specific tariffs (for solar panels, topic 7; for agriculture, topic 11), the WTO (topic 13), manufacturing plants (topic 15), and currency manipulation (topic 18) align with some of the statement/argument frames that I ultimately studied. However, certain topics still have the issue of being almost completely consumed by one media (e.g., TV or print).

Topic 1 Top Words:
Highest Prob: china, sea, south, taiwan, island, claim, beij
Score: sea, taiwan, island, navi, south, territori, reef
Topic 2 Top Words:
Highest Prob: percent, trade, market, year, stock, deficit, china
Score: stock, percent, index, price, dow, investor, deficit
Topic 3 Top Words:
Highest Prob: chines, compani, govern, said, china, offici, secret
Score: trademark, secret, compani, hack, hacker, indict, ivanka
Topic 4 Top Words:
Highest Prob: trump, donald, campaign, clinton, republican, presidenti, polici
Score: trump, clinton, donald, republican, hillari, candid, presidenti
Topic 5 Top Words:
Highest Prob: global, world, china, economi, nation, countri, intern
Score: ivori, emiss, eleph, africa, climat, greenhous, imf
Topic 6 Top Words: [NYT]
Highest Prob: new, section, time, york, word, length, document
Score: section, bylin, length, york, column, document, desk
Topic 7 Top Words:
Highest Prob: chines, china, import, solar, product, trade, panel
Score: solar, panel, tariff, duti, subsidi, manufactur, steel
Topic 8 Top Words:
Highest Prob: obama, presid, hous, administr, senat, bush, white
Score: obama, romney, senat, republican, bush, mitt, barack
Topic 9 Top Words: [NP]
Highest Prob: trade, deal, agreement, free, american, job, negoti
Score: agreement, trans-pacif, tpp, partnership, free, pact, deal
Topic 10 Top Words: [CNN]
Highest Prob: citi, china, trade, chines, first, year, student
Score: citi, student, cuba, museum, auction, ancient, school
Topic 11 Top Words:
Highest Prob: tariff, china, import, billion, trump, trade, product
Score: tariff, soybean, farmer, aluminum, pork, corn, agricultur
Topic 12 Top Words:
Highest Prob: chines, china, meet, leader, presid, beij, two
Score: jinp, meet, visit, leader, summit, beij, relationship
Topic 13 Top Words:
Highest Prob: state, unit, trade, world, china, countri, european
Score: unit, state, european, union, export, wto, organ
Topic 14 Top Words:
Highest Prob: presid, obama, asia, region, minist, japan, econom
Score: obama, abe, minist, asia, prime, asia-pacif, region
Topic 15 Top Words:
Highest Prob: compani, busi, china, manufactur, said, million, chines
Score: compani, alibaba, manufactur, factori, invest, plant, job
Topic 16 Top Words:
Highest Prob: north, korea, nuclear, sanction, korean, south, iran
Score: korea, north, nuclear, korean, kim, pyongyang, sanction

Topic 17 Top Words: [TV]
Highest Prob: trade, china, chines, trump, tariff, said, beij
Score: tariff, trump, zte, mnuchin, impos, billion, technolog
Topic 18 Top Words: [Currency, CNN mostly]
Highest Prob: china, currenc, econom, chines, bank, dollar, countri
Score: currenc, yuan, manipul, renminbi, dollar, undervalu, geithner
Topic 19 Top Words: [TV]
Highest Prob: trump, presid, china, polici, donald, call, administr
Score: trump, presid, tweet, donald, putin, tillerson, matti
Topic 20 Top Words: [Fox]
Highest Prob: like, one, american, china, make, mani, can
Score: thing, seem, dont, much, know, that, can

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