The Political Economy of Trade Deliberalization: How the US-China Trade War Fueled Anti-Americanism in China*

Wenbiao Sha†

May 2023

Abstract

This paper studies the political economy consequences of de-globalization in the context of the US-China trade war. Exploiting variation in US-specific trade penetration across Chinese regions and the timing of the trade war, I find that the trade war had larger positive impacts on anti-Americanism and nationalism for Chinese citizens living in regions with a higher level of ex ante US trade exposure. I also provide supporting evidence on the impacts of the trade war on the economic status and information search behavior of citizens in differentially affected regions.

Keywords: the trade war, trust, nationalism, economic shocks, salience, social identity
JEL Classification: F13, F52, Z19

*This paper is a revised version of the first chapter of my Ph.D. dissertation. I am deeply indebted to my supervisor Albert Park for his encouragement, support, and advice throughout this project. I am grateful to Li Han, Jean Hong, Ruixue Jia, James Kung, Sujata Visaria, and Noam Yuchtman for their comments that improved this paper greatly. I also thank Jiaying Chen, Robin Gong, Guojun He, Kohei Kawaguchi, Yatang Lin, Dan Lu, Wei Luo, Wenfang Tang, Shufei Wang, Lingwei Wu, Xianqiang Zou, and seminar and conference participants at HKUST Applied Micro Seminar, Wuhan University, Jinan IESR, The DSE Winter School, SYSU, SWUFE RIEM, AMES 2022 China, The 6th CCER Summer Institute, AMES 2022 Tokyo, and Political Science Speaker Series for Chinese Scholars for helpful comments and suggestions. All remaining errors are my own.

†Lingnan College, Sun Yat-sen University. Email: wenbiao.sha@outlook.com.

1 Introduction

Recent years have witnessed a backlash against globalization (mainly, trade and immigration), which is characterized by political realignment and ideological repositioning among citizens and exemplified by prominent political events such as Trump's success in the 2016 US presidential election (Autor, Dorn, Hanson and Majlesi, 2020) and the Brexit (Colantone and Stanig, 2018a).[1] Scholars have argued that social identity has played a central role in shaping the political economy consequences of globalization and in particular identity politics give a rise to anti-globalization policies favored and implemented by extremist politicians (e.g., Besley and Persson, 2021; Bonomi, Gennaioli and Tabellini, 2021; Grossman and Helpman, 2021). One such example is Trump's unilateral launch of the trade war against China from the beginning of 2018.

Given that the US-China trade war has become one of the largest international conflicts in recent decades, which some have called "the New Cold War" (Yao, 2021),[2] and that some have argued that China cannot rise peacefully and there would be inevitable rivalry between China and America (Mearsheimer, 2014, 2021),[3] it is of considerable interest and paramount importance to examine how the public view such a high-stakes conflict between superpowers, and to consider the implications for global cooperation and development. In addition, while many have documented the sharp increase in unfavorable view of China in the US and other western countries (Silver, Devlin and Christine, 2020, 2021; Jin, Dorius and Xie, 2021, among others), relatively little attention has been paid to how the trade war has affected political attitudes (e.g., anti-foreign sentiment and nationalism) in China. In this study, I provide systematic empirical investigations on these issues. Specifically, this paper examines how Chinese citizens have responded to the US-China trade war, focusing on individuals' trust in Americans and nationalistic sentiment, with insights from social identity theory. Relatedly, the 2022 Russia-Ukraine War, accompanied by fierce tension between Russia and the western countries, also makes it an important contribution to study citizens' responses to conflicts between great powers.

Trust and nationalism are important in and of themselves. First, trust can facilitate cooperation and trade, reduce intergroup conflicts, and promote development and prosperity (e.g., Arrow, 1974; Fukuyama, 1995; Guiso, Sapienza and Zingales, 2009; Tabellini, 2010; Rohner, Thoenig and Zilibotti, 2013).[4] In contrast, mistrust has well-documented negative political and economic consequences that can persist for long periods of time (e.g., Larson, 1997; Kydd, 2005; Nunn, 2008; Nunn and Wantchekon, 2011).[5] Second, nationalism is an important political ideology (Heywood,

[1] See Rodrik (2021) for a review on how globalization fuels populism around the world, and Colantone and Stanig (2019) for a review on how adverse globalization shocks contribute to the rise of nationalistic and radical-right parties in Europe. Also, see Caiani and Parenti (2016) for the rise of right-wing extremism groups in the US and Europe.

[2] See Yao (2021) for a detailed description and analysis for the New Cold War between the US and China. Additionally, two examples stand out. First, Pompeo made a surreal speech on July 23, 2020 in California, challenging the ideological foundation of the Chinese political system (see: `https://bit.ly/3AxO5z3`, last access on August 17, 2021). Second, there has been some nuclear weapon competition between the US and China in recent years, for example, see Cunningham (2021). Both examples illustrate some of the key features of the Cold War between the US and the Soviet Union.

[3] This is referred to as "the tragedy of great-power politics."

[4] This strand of literature is relatively large. See Algan and Cahuc (2014) for a comprehensive review.

[5] Mistrust serves as a channel through which the slave trade had a significant negative effect on long-term economic development in Africa (Nunn, 2008; Nunn and Wantchekon, 2011). Closely related to the research setting of this paper, some scholars have argued that mistrust that impeded cooperation among countries was the key reason why the Cold War had neither ended earlier nor taken a different path rather than intensive arms race (e.g., Larson, 1997; Kydd, 2005).

2017). In the Chinese context, nationalism has been proven to have profound impacts on political and economic outcomes (e.g., Johnson, 1962; Fisman, Hamao and Wang, 2014; Che, Du, Lu and Tao, 2015; Chen and Kung, 2020; Ouyang and Yuan, 2021).[6] For instance, Che et al. (2015) find that Chinese regions where experienced greater damage in the Sino-Japan war during 1937-1945 receive smaller Japanese investment and import less from Japan today and they also view Japan more unfavorably and have less trust in Japanese.

Empirically, this study exploits regional variation in US trade penetration across Chinese regions (cities or provinces) and the sharp timing of the US-China trade war. I employ two approaches to measure the trade war shocks. First, I combine spatial variation in US-specific trade openness (i.e., (export+import)/GDP) with plausibly exogenous variation in the timing of the trade war (i.e., a dummy for year 2018). The second approach exploits tariff changes, combining variation in predetermined local employment structure with presumably exogenous increases in tariffs imposed by the US on Chinese exports in 2018. As for the two main outcomes, I obtain individual-level panel data on trust in Americans from the China Family Panel Studies (CFPS) for 2012, 2014, 2016, and 2018, and individual-level repeated cross-sectional data on nationalism in China from the World Values Survey (WVS) for 2013 and 2018. The geographic information is available at the city (provincial) level for the CFPS (WVS) data, the trade war shock measures are constructed at the city and provincial levels for the trust and nationalism data, respectively. For both surveys, most respondents were surveyed in July and August of 2018 (see Appendix Figure A5). Thus, this paper studies the short-term effects of the US-China trade war, which intensified in subsequent years. US-China conflicts also extended beyond trade to restriction on China's high-tech firms and aggressive criticism on China's human rights. Thus, the actual impact of the US-China deteriorated relations is much greater than reflected in this study, especially in the long-run.

The two empirical strategies exploit rich spatial variation in trade with the US before the trade war and the sudden shock of the US-China trade war, both of which are essentially a shift-share design. Therefore, the main identifying assumption is that the levels of the exposure measures (trade or tariff) do not predict changes in the outcomes of interest prior to the trade war. While I only have one period of data on nationalism before the trade war, regression results obtained using three pre-trade war periods of data on trust show that the levels of neither trade exposure nor export tariff can predict changes in trust in Americans (see Appendix Table A4), lending strong support to causal identification of this paper. In addition, the trade war attracted Chinese citizens' attention only after it was announced by the Trump administration in March 2018; before then, Chinese citizens barely (almost do not) search for information about the trade war (see Panel A of Figure 7). This to a large extent supports that the timing of the trade war is exogenous to Chinese citizens.

Turning to the empirical findings, I begin by reporting the results on the pre-trade war relationships between trade exposure and trust and nationalism. I find that prior to the trade war, Chinese citizens exposed more to trade with the US had more trust in Americans and were less nationalistic compared to those with a lower level of trade exposure, consistent with the literature on the positive (negative) relationship between trade and trust (nationalism) (e.g., Rohner et al., 2013; Lan and Li, 2015).

[6] See Johnson (1962) and Chen and Kung (2020) for how nationalism contributed to the rise of communism in China. See Fisman et al. (2014), Che et al. (2015), and Ouyang and Yuan (2021) for the role of nationalism in influencing the relationship between historical experience of Sino-Japanese war and today's trade and economic outcomes.

The main finding is that holding other things constant, the trade war had a larger negative impact on trust in Americans of Chinese citizens in regions with a higher level of ex ante trade exposure and a larger positive impact on their nationalistic sentiment. The baseline estimates show a non-trivial impact of the trade war, no matter how one measures the trade war shocks. For trust in Americans, based on estimates obtained from specifications with individual fixed effects, the effect size amounts to about 4%-7% of the standard deviation of trust in Americans for a city with trade exposure in 2017 or export tariff change from 2017 to 2018 ranked at the 90th percentile of the corresponding distributions. By the same token, the effect magnitude is equivalent to around 0.28-0.44 standard deviations of nationalism for a province ranked at the 90th percentile of the distributions of the trade exposure in 2017 or the export tariff change between 2017 and 2018.

Next, I provide evidence for two possible channels. First, the empirical evidence shows that the trade war has a significant adverse impact on workers in cities exposed more to the trade with the US, using data on employment and wage income from the CFPS. This finding is consistent with Chor and Li (2021). These results suggest that greater exposure to adverse economic consequences may lead to more negative political responses for Chinese citizens in regions hit harder by the increased tariffs. Second, I show that there was a significant jump of media report on the trade war as well as individual search of relevant information on Baidu in March 2018 when Trump administration officially planned to impose China-specific tariffs. In addition, citizens in regions with more ex ante trade with the US are more likely to search for information about the trade war. This could reinforce the salience of nationalistic sentiment, since state-owned media as the major supplier is likely to present information about the trade war in a way that is critical of the US and portray the trade war as a US attack on China. The results suggest that there might be a salience impact under such an information environment.

Interestingly, I find heterogeneous effects on the labor market outcomes but not on trust and nationalism with respect to gender, education, birth cohort, and sector of employment (whether one works in the manufacturing sector), and flexibly accounting for sector fixed effects does not change the baseline results. That is to say, The negative political impacts are localized and do not differ across individuals within the same city. The fact that the heterogeneity in the labor market impacts did not translate into corresponding heterogeneous political effects implies that there could be other factors at work in addition to how severe one was affected by the trade war, because it suggests that citizens care about the payoffs of the city as a whole (not just their own self-interests).

To better understand the empirical patterns documented in this paper, I offer a simple model of trade and identity (see Section 6.3 for a detailed description and Appendix B for the model), following Shayo (2009) and Grossman and Helpman (2021). From a broader perspective, the starting point of the model is global human identification (i.e., identifying with all human beings),[7] a phenomenon mostly studied by social psychologists which is believed to be useful in tackling global challenges (Reese, Rosenmann and McGarty, 2015),[8] such as environmental concerns (Reese, 2016). Relatedly, economists have also argued that international integration and broader social identification are interrelated and may reinforce one another (Abramson and Shayo, 2022), and that incumbent parties dominated by cosmopolitans could lead to greater support for liberal policies

[7] See McFarland, Hackett, Hamer, Katzarska-Miller, Malsch, Reese and Reysen (2019) for a detailed discussion on the concept of global human identification.

[8] Also, see Rosenmann, Reese and Cameron (2016).

favoring immigration (Besley and Persson, 2021). I argue that such a globalized (or encompassing) identity was fostered among Chinese citizens in regions with high foreign trade penetration, which often is accompanied by cultural exchanges (e.g., watching Hollywood movies). This may not be surprising given that China's foreign trade has increased dramatically since the late 1970s, while before then China had almost zero foreign trade.[9] In this regard, complementing studies on the role of social identity in influencing the globalization backlash, this study examines the importance of social identity for understanding the political economy consequences of de-globalization, without ignoring the complexity of the globalization process.

In the model, I consider a 2×2 setting: two regions with differential levels of trade penetration (high versus low) and two social identities (US-friendly versus nationalistic), in which regions are associated with types of individuals in society. When one identifies with a certain social group, her utility will consist of three components: individual income, group status proxied by an average member's income, and perceived distance depending on how similar she is compared to a prototypical group member in terms of prominent attributes and/or prescribed norms. As noted earlier, I assume that a person's perception of group status is based on the experience of people living in her own region, which is supported by the finding that there are heterogeneous economic effects but no heterogeneity in the political impacts. Clearly, the trade war could affect group status through the labor market and awaken the salience of national identity that is crucial in determining the perceived distance as Chinese people perceive it as a US attack on China and a trade bully and their attention is shifted from economic to cultural conflicts. The model delivers two sets of predictions. First, before the trade war, citizens in regions penetrated more by the trade with the US are more likely to be US-friendly. Second, after the trade war, citizens in regions doing more trade with the US are more likely to switch their identity from the US-friendly to nationalistic group, through two social identification channels: lower group status and greater perceived distance. The empirical results are largely consistent with the theory (see Section 6.3 for more detailed discussion).

This paper contributes first to the literature studying the political economy consequences of trade (or globalization more generally). International trade has been found to reduce domestic nationalism, for example, Lan and Li (2015) show that accession to WTO has weakened nationalism in China. Trade has also been found to cause political polarization in the US (Autor et al., 2020), economic nationalism in the Western Europe (Colantone and Stanig, 2018b, 2019), support for the Brexit in the UK (Colantone and Stanig, 2018a), and violent crimes in Mexico (Dell, Feigenberg and Teshima, 2019) as well as in Brazil (Dix-Carneiro, Soares and Ulyssea, 2018). Additionally, globalization contributes to rising populism (see Rodrik (2021) for an excellent review). Meanwhile, export slowdown has increased labor strikes in China (Campante, Chor and Li, 2020). This strand of literature indicates that the uneven distributional consequences of trade shocks within a country can fuel protectionism, isolationism, extremism, and violence (see Rodrik (2021) and Colantone, Ottaviano and Stanig (2021) for surveys with detailed discussion). This paper complements this large literature by examining the adverse political effects of the US-China trade war (i.e., a trade

[9] Because export and import can have differential economic impacts (say, depending on the preexisting labor market structure), it is not obvious that trade could always cultivate a globalized identity in China. However, it may not be surprising if we recognize that China started the opening-up policies from a situation with almost no trade with other countries in 1978, but since then its foreign trade has grown dramatically, so China has enjoyed more benefits than losses in the past several decades. See Yu (2020) for China's trade development from 1978 onward.

deliberalization event). Complementary to this paper focusing on Chinese citizens' attitudinal responses to the trade war, Fan, Hu, Tang and Wei (2022) find that the trade war also reduces Chinese citizens' consumption of US movies, which is a behavioral response.

Second, this paper adds to the emerging studies on social identity, which was first introduced into economics by Akerlof and Kranton (2000, 2010). Scholars have shown that social identity theory is a powerful framework for understanding many political economy phenomena, including redistribution preferences (e.g., Shayo, 2009; Klor and Shayo, 2010), nation building (e.g., Depetris-Chauvin, Durante and Campante, 2020), conflicts and violence (e.g., Sen, 2007; Sambanis and Shayo, 2013; Tezcür, 2016; Atkin, Colson-Sihra and Shayo, 2021), judicial bias (e.g., Shayo and Zussman, 2011), and political competition (e.g., Eifert, Miguel and Posner, 2010).[10] In particular, following recent studies linking identity politics to the backlash against globalization (e.g., Besley and Persson, 2021; Bonomi et al., 2021; Grossman and Helpman, 2021), this paper studies the role of identity in shaping Chinese citizens' responses to the US-China trade war. Additionally and relatedly, this study provides empirical evidence on how common experiences occurred at the regional level (more trade with the US or a more international environment more generally in this paper) can foster a regional identity (a US-friendly identity or globalist), consistent with the findings of Dehdari and Gehring (2022), and how external threats or shared nationwide experiences could foster a national identity or nation-building more broadly (e.g., Dell and Querubin, 2018; Depetris-Chauvin et al., 2020), or even an identity with more broadly defined membership, such as a European Union identity (Gehring, 2022).

Third, to the best of my knowledge, this study provides the first quantitative causal evidence on how large-scale international conflicts may foster an environment of mistrust (specifically, reduction in Chinese citizens' trust in Americans), which has been argued to have played an important role in the Cold War (e.g., Larson, 1997; Forsberg, 1999; Kydd, 2005). More broadly, this paper complements the literature studying international conflicts and public opinion (e.g., Frye, 2019; Jin et al., 2021). Last, this paper speaks to the literature on the relationship between national threats from (or invasions by) foreign powers and nationalism in China (e.g., Gries, Zhang, Crowson and Cai, 2011; Fisman et al., 2014; Che et al., 2015; Chen and Kung, 2020; Yue, 2020).

The remainder of this paper is structured as follows. Section 2 presents the background information of the US-China trade war. Section 3 introduces the data. Section 4 explains two empirical strategies. Section 5 reports the baseline results and robustness checks. Section 6 provides evidence for the possible channels and presents a framework of trade and identity as a unified explanation. Section 7 concludes the paper.

2 The US-China Trade War

2.1 US-China Bilateral Trade

Since economic reforms and opening-up started in 1978, China has achieved remarkable growth (e.g., Yao, 2014). International trade is widely believed to have contributed significantly to this

[10] See Shayo (2020) for a comprehensive review. Also, see Akerlof and Kranton (2005) for an earlier review and Charness and Chen (2020) for a survey of the experimental literature on social identity.

process. Indeed, China has become the world's largest trading country (the largest exporter since 2009 and the largest importer since 2015). Moreover, China's foreign trade volume has increased more than 200-fold over the past four decades, while its GDP has only grown about 34-fold (Yu, 2020). Research has shown that Chinese firms have benefited greatly from trade liberalization (e.g., Brandt, Van Biesebroeck, Wang and Zhang, 2017).

The US has been the most important trading partner of China for a long time, especially after China's accession to the WTO. Soon after China's opening-up, the US granted "Most Favored Nation" (MFN) status to China in 1980. Conditionality of status was ended in 1999 when the US further granted China "Permanent Normal Trade Relations." Finally, China joined the WTO in 2001. The US is the largest export destination for China today.

[Figure 1 about here]

Panels A and B of Figure 1 plot China's exports to and imports from the rest of the world (including the US) and the US only for the period 2000-2019. One can see that China has run trade surpluses since its accession to the WTO, and that most of this surplus is due to the large bilateral trade surplus with the US. During 2000-2019, China's exports to the US grew rapidly, and the growth of China's imports from the US also increased but not as dramatically. In addition to the large trade imbalance, another notable feature of US-China trade is that China has mainly exported labor-intensive products to the US.

Chinese regions exporting more to the US today are concentrated in coastal regions, especially the Yangtze River Delta and Pearl River Delta.[11] The special economic zones offering a package of preferential policies to foreign companies were first established in Guangdong and Fujian (two coastal provinces) in 1980, and then gradually expended to other coastal cities and then to inland provinces. China later established a free trade zone in Shanghai in 2013 and then to three other coastal cities in 2015, seven more cities in 2016, six of which were inland cities. The growth of export-oriented manufacturing has delivered significant benefits to Guangdong Province, China's largest exporting province.

2.2 The US-China Trade War

The large trade imbalance between the US and China was the most important reason for Trump to launch the trade war against China. Trump argued that the trade deficit hurt the US economy and was mainly caused by China's "unfair trade practices." The US imposed high tariffs on imports from China in order to bring manufacturing jobs back to the US.

The trade war has been carried out mainly as a tariff war, which was triggered in March 2018 when the Trump administration unilaterally announced the plan of imposing a 25% tariff on $50 billion worth of imports from China from July 6, 2018 onwards.[12] China retaliated by imposing tariffs on imports from the US, following the principle of "equal size and equal proportion." This quickly escalated into a large-scale tariff war between the two countries. The escalation did not stop until September 1, 2019 when the US (China) placed higher tariffs on more than $550 ($185) billion

[11] See Appendix Figures A1 and A2 for regional distribution of exposure to the trade with the US based on trade openness and export tariffs, respectively.

[12] See Yu (2020) and Fan (2021) for more detailed analyses pertaining to tariff evolution of China and the US.

of imports from China (the US). We can observe from Panel A of Figure 2 that the trade volume between China and the US dropped significantly in 2019. Additionally, average tariff levels nearly tripled as a result of the trade war (see Panel B of Figure 2). In this figure, the 2018 average tariff rate is based on tariffs announced as well as imposed by the end of 2018. One also can see that the tariff rates appear to flatten out during 2005-2017, which suggest that the sudden increase of tariffs in 2018 was unexpected.

[Figure 2 about here]

The trade war also evolved into a tech war.[13] The Trump administration accused China of unfairly transferring American technology, stealing intellectual property, and threatening US national security. The Trump administration restricted Chinese companies' investment in US high-tech firms and placed Chinese companies on the US Bureau of Industry and Security's Entity List. Trump banned US firms from doing business with Chinese information and communication technology (ICT) company ZTE in 2018, which was later reversed after progress was made in trade negotiation with China. A year later in 2019, the Trump administration put Huawei on the Entity List. From then on, China did not compromise in the trade talks as nationalistic sentiment was brightened (Tiezzi, 2019). In 2020, Trump's pressure to force TikTok to sell its US business to Microsoft further spurred outrage and nationalism among Chinese citizens (Shen, 2020).

These actions taken by the Trump administration were widely perceived by China's governments and its citizens as being unjustified and bullying behavior. The Chinese government accused the US of abusing export control measures and making "national security" a catch-all justification without evidence or explanation (BBC, 2019; Tiezzi, 2019). The strong sense of injustice led to the breakdown of trade talks in May 2019. Researchers questioned whether the trade imbalance was hurting the US economy, since Chinese exports were of good quality and sold at low prices, and China balanced the trade surplus by purchasing US Treasury bonds using its foreign reserves (e.g., Sheng, Zhao and Zhao, 2019; Yu and Zhang, 2019; Yu, 2020). These views reinforced the feelings of many Chinese that China was being attacked unfairly by the US.

3 Data and Measures

3.1 Measuring the Trade War Shock

This paper employs two ways to measure the trade war shock, both exploiting rich spatial variation in ex ante trade with the US and the unexpected sudden change caused by the US-China trade war. The first focuses on trade openness, whereas the second exploits tariff rate changes. For both approaches, I construct both city-level and one provincial-level measures because geographic information is available at the city level for the trust data, and at the provincial level for the nationalism data. In what follows, I focus on how the city-level measure is constructed, which is the same as the method used to construct the provincial measures.

US-Specific Trade Exposure. First, I draw on data from the China's General Administration of Customs, which covers the universe of Chinese exports and imports, to construct the trade exposure

[13] See Sun (2019) for more detailed discussion on the US-China tech war.

variable. First, I only include exports to the US or imports from the US. I aggregate across the data to the city-year level (city c in year t) to calculate exports to the US ($ExpUS_{ct}$) and imports from the US ($ImpUS_{ct}$). Finally, weighted by GDP, I calculate the trade exposure measure as follows, where I define US trade exposure to be the ratio of exports plus imports to GDP:

$$TradeExposure_{ct} = \frac{ExpUS_{ct} + ImpUS_{ct}}{GDP_{ct}}. \tag{1}$$

In describing city-year specific trade exposure, two patterns emerge. First, most of the variation is cross-sectional. As depicted in Figure 3, the 2010 trade exposure measure is strongly positively correlated with the 2017 one (the fitted regression line almost resembles a 45-degree line with an R-squared larger than 0.8). Second, cities that have higher exposure to the trade with the US are concentrated in the coastal region (see Appendix Figure A1),[14] consistent with China's development trajectory. To combine temporal variation in the timing of the trade war with trade exposure, I further interact its lag (by one period) with a dummy for 2018: $TradeExposure_{c,t-1} \times \mathbf{1}(t = 2018)$. Note that taking lag alleviates concerns of reverse causality. Now the interacted variable makes it possible to compare outcomes in high-trade regions before and after the trade war with changes among individuals in low-trade regions over the same period.

[Figure 3 about here]

US Tariffs on Chinese Exports. Given that the US-China trade war has been occurring mainly through raising import tariffs, my second measure of the trade war shock is a measure of exposure to tariff changes. Data on tariff changes comes from two sources. I first construct a measure of export tariff levels by industry (defined at the 3-digit Chinese Industrial Classification (CIC) level) and by year from two sources. Data on regular tariff levels is obtained from the World Integrated Trade Solution (WITS, see: https://wits.worldbank.org/), while data on tariff increases imposed by the US government is collected from announcements and documents of the Office of the United States Trade Representative (USTR, see: https://ustr.gov/). For the latter, I only consider tariffs that were effective by the end of 2018.[15] Both data sets are originally at the HS 8-digit level. I map them into 3-digit CIC level using a concordance table.[16] Combining these two data sets yields a measure of US tariffs on Chinese exports ($USTariff_{jt}$) for industry j in year t. This captures the sharp change in tariffs caused by the trade war, as shown in Figure 2.

Next, to construct a city-level tariff measure, I weight the tariffs in different industries by the ratio of the number of workers in industry j of city c ($Workers_{cj,2010}$) to the number of total workers in city c ($Workers_{c,2010}$), both measured using data from China's 2010 census. To alleviate concern that local employment structure does not fully capture the importance of trade in each sector, I also consider the importance of a given industry's exports relative to national exports by using per worker exports to the US of industry j ($ExpUSPer_{jt}$) as a share of overall per worker exports to the US ($ExpUSPer_t$) as weights.[17] Last, the export tariff measure is constructed for city c in year t in the

[14] Also, see Panels A and B of Appendix Table A3 for the distribution of the measures.

[15] That is, I exclude tariffs that were announced yet imposed by the end of 2018.

[16] A simple average will first be taken when one CIC 3-digit level is corresponding to multiple HS 8-digit levels.

[17] Fixing time in 2010 (i.e., using $ExpUSPer_{j,2010}$ and $ExpUSPer_{2010}$) does not change the baseline results. See Appendix Table A1.

following way:

$$ExportTariff_{ct} = \sum_j \frac{Workers_{cj,2010}}{Workers_{c,2010}} \frac{ExpUSPer_{jt}}{ExpUSPer_t} USTariff_{jt}. \quad (2)$$

Appendix Figure A2 plots the spatial distribution of changes in the export tariff measure from 2017 to 2018 (i.e., $ExportTariff_{c,2018} - ExportTariff_{c,2017}$), visualizing its regional variation.[18] Similar to Appendix Figure A1, the cities most heavily hit by increased US tariffs in 2018 are in the coastal region. It is worth noting that while the trade exposure measure broadly captures the extent to which a city's social and economic activities and people living in that city are influenced by the trade with the US, the variation in export tariff measure comes from the initial labor market conditions across cities.

3.2 Trust, Nationalism, and Other Variables

The outcomes of interest and related control variables used in this paper are mainly obtained from the China Family Panel Studies (CFPS, see: https://www.isss.pku.edu.cn/cfps/en/) and the World Values Survey (WVS, see: https://www.worldvaluessurvey.org/). The CFPS, launched in 2010 and conducted by Peking University, is a nationally representative longitudinal survey in China, with a large sample size and panel structure. I use its most recent four waves (2012, 2014, 2016, and 2018) which contain questions about trust in Americans. The WVS was started in 1981 and has been operating in more than 120 societies around the world. I use its China survey and the most recent two waves (2013 and 2018). Geographic information for the CFPS and WVS are available at the city and provincial levels, respectively. Below I describe the variables in detail.

CFPS and Trust in Americans. I obtain data on Chinese citizens' trust in Americans from the CFPS. The CFPS survey asks respondents about the degree to which they trust Americans and ask them to choose a number between 0 (extremely low trust) and 10 (extremely high trust). Thus, the trust outcome is an ordinal variable that varies at the individual level. Information on this outcome is available in 2012, 2014, 2016, and 2018 for family members aged 10 or above. Taken together, the CFPS enables me to construct a national individual-level panel data set. In the trust regressions, I control for age dummies, and eduction-level dummies, in addition to individual and time fixed effects.

WVS and Nationalism. Data on nationalism comes from the WVS. I employ a principal component analysis method to obtain a nationalism index based on the following three statements that measure different dimensions of nationalism: *(i)* how proud are you to be Chinese? (not at all proud = 1, not very proud = 2, quite proud = 3, very proud = 4); *(ii)* do you consider strong defense forces as the most important goal of China (relative to a high level of economic growth, seeing that people have more to say about how things are done, and trying to make our cities and countryside more beautiful)? (no = 0, yes = 1); and *(iii)* would you be willing to fight for China if there will be another war? (no = 0, yes = 1).[19] The finalized data set from the WVS is an individual-level two-year (2013 and 2018) repeated cross-section with national coverage. In the nationalism regressions, I

[18] Also, see Panels C and D of Appendix Table A3 for the distribution of the export tariff changes.

[19] See Appendix Table A2 for the construction detail. My approach is closely related to the one employed by Lan and Li (2015) who also use the WVS data to construct a nationalism index for Chinese provinces.

control for gender dummy, age dummies, education-level dummies, and provincial and time fixed effects.

Labor Market Outcomes. When examining the effects on the labor market, I use data on two labor market outcomes from the CFPS. The first is an employment dummy indicating whether one is employed or not at the time of the survey. The second is annual wage income (in logs). For this exercise, I restrict the sample to working age population only (ages 16-64) and exclude current students.

Additional Placebo Outcomes. In the empirical analysis, I conduct a placebo test using data on trust in strangers from the CFPS and trust in foreigners from the WVS. Both are categorical variables. The former ranges from 0 (low trust) to 10 (high trust), while the latter ranges from 1 (low trust) to 4 (high trust).

City or Provincial GDP. Given that the treatment variable (trade exposure measure or export tariff measure) varies either at the city level for trust regressions or at the provincial level for nationalism regressions, I also control for city or provincial GDP per capita (logged), for which data is available from the Chinese City and Provincial Statistical Yearbooks, respectively.

3.3 Baidu Indices and Broadband Internet

To study the role of information, I draw on data from Baidu, the largest search engine and an important information source in China, and data on access to the Internet from the City Statistical Yearbooks.

Baidu Indices. In China, many people rely on Baidu to obtain information, especially when they want to find specific information on an particular topic, users can search using keywords. Baidu provides three indices for any keywords once it gets enough attention and interest (similar to Google Trends),[20] but only one is available at city level during the period spanning the trade war. I use data from the Baidu search index, an index which captures the frequency of searching any keywords on Baidu. The keywords I focus on in this paper are "US-China trade war" or "trade war" (Chinese: "*Zhongmei Maoyizhan" or "Maoyizhan*"). Thus, the Baidu search index directly measures the demand for information pertaining to the trade war. This Baidu search index data is available on a daily basis from 2011 onwards. I aggregate the data to the monthly- or yearly-level in the empirical analysis, depending on the unit of analysis in the regressions. Additionally and more importantly, Baidu provides geographic information on searches at the city level, which enables me to conduct city-level analysis.

Moreover, Baidu provides an information-flow index, reflecting Baidu users' behavior (reading, commenting, forwarding, likes, and dislikes etc.) regarding news, posts, and reports about the trade war. At the national level, it is available starting from July 2017, while at the city level it is available only from June 2018. Last, the third index provided by Baidu counts the frequency of news articles with titles mentioning the keywords "US-China trade war" or "trade war", reflecting information supplied by Chinese media. It is available only at the national level.

Broadband Internet. To be able to search on Baidu, one has to have access to the Internet, which I will take into account by using data on broadband Internet across cities from China's City

[20] For Baidu, see: https://www.baidu.com/; for Baidu index, see: https://index.baidu.com/.

Statistical Yearbooks, measured as number of households having access to broadband Internet.

3.4 Summary Statistics

Table 1 presents the summary statistics for key variables, including trade war shock measures and main outcomes. Panel A shows the descriptive statistics for both city- and provincial-level measures of trade war shocks. For the US-specific trade exposure measure, the city-level average is about 0.02 during the 2010-2017 period, while the provincial-level average is higher, at 0.04.[21] Both exhibit a downward trend over time (higher in 2010 than 2017), mainly because China's GDP grows faster than foreign trade during the period. For the export tariff measure constructed from US tariffs on Chinese exports, the city- and provincial-level averages are 0.04 and 0.03 during the period 2010-2018, and are about three- and four-time larger in 2018 than in 2017. This measure changes little during 2010-2017.[22] Using a similar approach, I also construct import tariff measures, which show similar descriptive patterns but have higher absolute values than the export tariff measures do. This is because in general China's tariffs on imports from the US are higher than tariffs imposed by the US on China's exports to the US (see Figure 2).

[Table 1 about here]

In Panel B of Table 1, one can see that the mean of Chinese citizens' trust in Americans is about 2.42 on a scale of 0-10, and the mean of the nationalism index is around 2.63 with a min of 0.6 and a max of 3.5.[23] Apparently, the distribution of trust in Americans is right-skewed, and the distribution for the nationalism index is left-skewed (see Appendix Figure A4 for densities).[24] In the regression analysis, I standardize both outcomes (subtract mean and divide by the standard deviation). In analyzing the channels below, I focus on labor market outcomes (Panel C) and the Baidu search index (Panel D). We see from Panel C that China's average non-working rate is about 25% for the years 2012, 2014, 2016, and 2018. Log annual wage income has a mean of 7.3. In Panel D, the Baidu search index measures how frequently people search for "US-China trade war or trade war" on Baidu. One can see that the city-level Baidu search index normalized by population really surges in 2018. I provide summary statistics for other variables used in this paper in Appendix Table A3. Throughout the paper, refer to Table 1 and Appendix Table A3 for data sources.

4 Empirical Strategies

This section mainly describes two baseline empirical strategies, one focusing on exposure to trade with the US and the other utilizing changes in US tariffs on Chinese exports. Both exploit rich spatial variation in trade with the US before the trade war and the sudden shock of the US-China trade war.

[21] This is mainly due to that some cities have a value of zero in some years, while it is not the case for provinces.

[22] For example, see Figure 2, in which the tariff levels are constructed in a simpler manner.

[23] Using the same data source—the WVS, my approach constructing the nationalism index is similar to the one employed by Lan and Li (2015). My approach yields an index with a slightly higher mean than theirs.

[24] Although the nationalism index is constructed from three variables, its left-skewed distribution (i.e., a general high level of nationalism in China) is consistent with what scholars have documented using different data sources (e.g., Tang and Darr, 2012).

4.1 US-Specific Trade Exposure

My first empirical strategy combines cross-regional variation in trade openness with temporal variation caused by the trade war. As mentioned earlier, since data on trust and nationalism come from different sources with different geographic scope and year coverage, the corresponding estimating equations are slightly different.

To examine effects on trust in Americans, I estimate the following equation for individual i in city c in year t (essentially, a difference-in-differences framework), using four-year panel data:

$$\begin{aligned} Trust_{ict} = \alpha \times TradeExposure_{c,t-1} \\ + \beta_{2012} \times TradeExposure_{c,t-1} \times \mathbf{1}(t = 2012) \\ + \beta_{2014} \times TradeExposure_{c,t-1} \times \mathbf{1}(t = 2014) \\ + \beta_{2018} \times TradeExposure_{c,t-1} \times \mathbf{1}(t = 2018) \\ + (X_{ict}, Z_{ct})'\sigma + \lambda_i + \delta_t + \varepsilon_{ict}, \end{aligned} \tag{3}$$

where $TradeExposure_{c,t-1}$ is defined by Equation (1), which measures a given city's exposure to trade with the US in a given year. $TradeExposure_{c,t-1}$ is further interacted with time dummies. The interaction between trade exposure and the 2016 dummy is omitted and used as reference group in the regressions since 2016 is the last survey wave prior to the trade war. I take one-period lag of this treatment variable to alleviate concern that trust facilitates trade, leading to reverse causality. (X_{ict}, Z_{ct}) is a vector of individual and city time-varying characteristics that could affect trust, including age dummies, education-level dummies, and log city GDP per capita. λ_i and δ_t are individual and time fixed effects, respectively. The former removes any time-invariant determinants of trust that are specific to each individual, while the latter further captures any differences in trust across time periods. The error term, ε_{ict}, is clustered by city, allowing for correlations across individuals within each city. β_{2018} is the coefficient of interest, capturing the effects of the US-China trade war on Chinese citizens' trust in Americans.

In this specification, identification comes from comparing changes in the same individuals' trust after the trade war for those in cities with high exposure to US trade with changes in trust among those in cities with low US trade exposure. The identifying assumption is that citizens in cities with high and low trade exposure follow similar pretreatment trends, as required by a difference-in-differences framework. In the specification, β_{2012} and β_{2014}, the coefficients on the interactions between trade exposure and time dummies preceding the trade war enable me to check whether the parallel pre-trends assumption holds or not.

Turning to nationalism, for individual i in province p at year t, I estimate an equation similar to Equation (3) using two years of repeated cross-sectional data (in 2013 and 2018):

$$\begin{aligned} Nationalism_{ipt} = \alpha \times TradeExposure_{p,t-1} \\ + \beta_{2018} \times TradeExposure_{p,t-1} \times \mathbf{1}(t = 2018) \\ + (X_{ipt}, Z_{pt})'\sigma + \lambda_p + \delta_t + \varepsilon_{ipt}, \end{aligned} \tag{4}$$

where now $TradeExposure_{p,t-1}$ is defined at the provincial level. Again, (X_{ipt}, Z_{pt}) is a vector of individual and provincial time-varying covariates, including gender dummy, age dummies, education-level dummies, and log provincial GDP per capita. λ_p and δ_t are provincial and time fixed effects, respectively. The former removes any time-invariant determinants of nationalism that are specific to each province, while the latter absorbs any temporal shocks that are common to all individuals. Following Lan and Li (2015), the error term, ε_{ipt}, is clustered at the province-year level, allowing for correlations across individuals within the same province in the same year. The coefficient of interest, β_{2018}, captures the effects of the US-China trade war on Chinese citizens' nationalistic sentiment.

Since the nationalism data is a repeated cross-section for two years only, I cannot control for individual fixed effects, nor can I control for provincial-level time trends. A causal interpretation again requires citizens in different provinces with differential levels of exposure to the trade with the US to have parallel trends prior to the trade war, which cannot be directly checked in this specification. Admittedly, compared to Equation (3), the results obtained from Equation (4) are less well identified.

4.2 US Tariffs on Chinese Exports

My second baseline empirical strategy combines variation in predetermined local employment structure in 2010 with presumably exogenous increases in US tariffs on Chinese exports in 2018. Depending on whether the outcome of interest is trust or nationalism, I estimate two equations similar to the above ones, replacing the trade exposure measures with export tariff measures. Specifically, when using trust as the outcome variable, the regression specification is as follows:

$$Trust_{ict} = \beta \times ExportTariff_{ct} + (X_{ict}, Z_{ct})'\sigma + \lambda_i + \delta_t + \varepsilon_{ict}, \tag{5}$$

where $ExportTariff_{ct}$ is the tariff level of a given city's exports to the US in a given year, as defined in Equation (2). The remaining regression terms are the same as in Equation (3).

The source of identification of this specification is illustrated in Panel A of Figure 4, which plots the time series of the export tariff measure for two cities: Dongguan of Guangdong Province and Yuxi of Yunnan Province. The former exports a lot to the US, whereas the latter does not. One can observe two patterns. First, Dongguan has a much higher level of export tariffs imposed by the US than Yuxi does even before the trade war. This difference is primarily driven by differences in employment structure in 2010. Second, while there is almost no change in tariffs before the trade war, there is a sudden, huge jump in 2018 for Dongguan, exogenously arising from Trump's tariff war against China and a much smaller increase in Yuxi. With individual and time fixed effects controlled for, the specification of Equation (5) identifies the difference-in-differences.

[Figure 4 about here]

As noted by Goldsmith-Pinkham, Sorkin and Swift (2020), this specification is a reduced-form shift-share design with Bartik-like instrument $ExportTariff_{ct}$. Thus, the identifying assumption is that the levels of tariff exposure do not predict changes in trust prior to the trade war. Given that the trade war induced a sharp policy change in 2018, we can test whether the exposure to the trade policy change measured by export tariff exposure or US trade exposure is associated with changes in trust. Following Goldsmith-Pinkham et al. (2020), using data on the pre-trade war period, I run regressions of trust on interactions between the exposure measures fixed in 2010 and time dummies with individual fixed effects controlled for. Appendix Table A4 reveals that none of the levels of tariff exposure and trade exposure are statistically significantly correlated with changes in trust before the trade war, suggesting that the levels of tariff/trade exposure are likely exogenous to changes in the outcomes of interest in my research setting.

Generally, unbiased estimation of β requires $E(\varepsilon_{ict}|X_{ict}, Z_{ct}, \lambda_i, \delta_t) = 0$ (i.e., conditional mean independence). That is, conditional on the baseline controls, the treatment of interest is uncorrelated with the error term. Given that the export tariff measure mainly exploits variation in predetermined local employment structure and exogenous variation in tariff evolution, the rich set of controls should satisfy the conditional mean independence assumption. Empirically, if one could obtain largely similar results using specifications with and without baseline controls, this also suggests that the difference-in-differences estimates are not severely biased (Altonji, Elder and Taber, 2005).

When using nationalism as the outcome variable, I estimate the following equation:

$$Nationalism_{ipt} = \beta \times ExportTariff_{pt} + (X_{ipt}, Z_{pt})'\sigma + \lambda_p + \delta_t + \varepsilon_{ipt}, \tag{6}$$

where $ExportTariff_{pt}$ is constructed at the provincial level and the rest of the specification is the same as in Equation (4). Similarly, Panel B of Figure 4 illustrates the variation in tariffs in a high-trade province (Guangdong) and a low-trade province (Yunnan). Unfortunately, due to the lack of data, I cannot test for the association between the exposure measures and changes in nationalism before the trade war.

4.3 Examining Information Search Behavior

To investigate who tends to search more information related to the trade war on Baidu, using city-level data on Baidu search index and access to broadband Internet during 2011-2018, I estimate the following equation for city c of province p in year t:

$$\begin{aligned} BaiduSearch_{ct} &= \tau \times ExportTariff_{ct} + \eta \times Broadband_{ct} \\ &\quad + \rho \times ExportTariff_{ct} \times Broadband_{ct} + \sigma \times GDP_{ct} + \lambda_c + \delta_{pt} + \varepsilon_{ct}, \end{aligned} \tag{7}$$

where $BaiduSearch_{ct}$ is the Baidu search index normalized by population, $ExportTariff_{ct}$ is the export tariff measure as defined in Equation (2), and $Broadband_{ct}$ is the number of households having access to broadband Internet, which also is normalized by population. I control for log city GDP per capita (GDP_{ct}) and city and province-by-year fixed effects (λ_c and δ_{pt}). The error term ε_{ct} is clustered at the city level. To interpret τ and η more meaningfully, both $ExportTariff_{ct}$ and $Broadband_{ct}$ are demeaned in the regressions.

In this specification, one should expect both τ and ρ to have positive signs as well as to be statistically significantly different from zero. First, in addition to citizens in different cities being motivated differently to pay attention to information about the trade war, they also may react more to information related to their economic interests (e.g., Hartzmark, Hirshman and Imas, 2021). Thus, citizens in high-trade regions are likely to demand more information pertaining to the trade war, which supports a greater impact on social identity choice. Additionally, technology can affect how much information one is capable of receiving. For instance, Internet infrastructure (e.g., broadband Internet) facilitates information acquisition and so could have political economy effects (e.g., Zhuravskaya, Petrova and Enikolopov, 2020). Thus, citizens in cities with better infrastructure may acquire information more easily and the information is likely to be presented in a nationalistic way.

5 Effects on Trust and Nationalism

In this section, I present evidence on the relationships between trade and trust and between trade and nationalism before the US-China trade war, the baseline results of the effects of the trade war on trust and nationalism (including long-term effects on trust), and the results of robustness checks.

5.1 Pre-Trade War Relationships

To examine the relationship between US-specific trade exposure and Chinese people's trust in Americans and their nationalistic sentiment prior to the trade war (Prediction 1), I estimate Equations (3) and (4), dropping the interaction terms. To make the empirical specifications consistent with the baseline strategy, I take the one year lag of the trade exposure measure.[25] Table 2 reports the regression results. Columns 1 and 3 do not include covariates (gender dummy, age dummies, educational-level dummies, and log city/provincial GDP per capita), which are controlled for in columns 2 and 4. Column 3 does not include year dummies because it only uses the 2013 wave of the WVS.

[Table 2 about here]

One can see from Table 2 that there is a strong positive (negative) association between regional trade exposure and trust (nationalism). Even after controlling for a rich set of individual characteristics (namely, gender, age, education, and income) and regional GDP per capita, we still can observe strong correlations that are statistically significantly different from zero (columns 2 and 4). Prior to the trade war, a one standard deviation increase in city-level US trade exposure is associated with a 0.08 standard deviation increase in trust in Americans (column 2), and a one standard deviation increase in provincial US trade exposure is associated with a 0.43 standard deviation decrease in nationalism (column 4). This result suggests that during the pre-trade war period, Chinese citizens in high-trade regions were more US-friendly, while those in low-trade regions were more nationalistic.

5.2 Effects of the Trade War

This subsection reports the baseline results of the effects of the trade war shocks on trust and nationalism, obtained from the two empirical strategies described above. Columns 1-4 of Table 3 present the estimated impacts on Chinese citizens' trust in Americans using Equation (3). I start with an individual-level panel regression with only individual and time fixed effects controlled

[25] Since variation in this variable is persistent over time and thus more of cross-sectional (see Figure 3), taking one-year lag does not remarkably change the results.

for (column 1), and then add individual- and city-level control variables, including age dummies, education-level dummies, and log city GDP per capita, to the panel regression (column 2). One may be concerned that people with different educational levels may have different responses over time, so I replace education-level dummies with education-by-year dummies in column 3. Column 4 uses a balanced panel, addressing the concern that sample composition changes over the study period could introduce bias. Notice that the outcome variable is standardized in both regressions. One can see that the estimated effects are very similar in terms of both magnitude and statistical significance. Focusing attention on the parsimonious specification with only individual and time fixed effects controlled for (column 1) and the estimated coefficient on the interaction term between trade exposure and the 2018 dummy, a one standard deviation increase in city-level US trade exposure is associated with a 0.03 standard deviation decrease in trust in Americans after the trade war. Moreover, the effect size amounts to 0.04 standard deviations of trust in Americans when evaluating the magnitude at the trade exposure level of a city ranked at the 90th percentile of the distribution of the 2017 trade exposure measure (e.g., Guangzhou City).[26] The effect size is much larger, about 0.16 standard deviations decrease in trust, if we evaluate the magnitude using the trade exposure level of Dongguan City in 2017, one of the Chinese cities doing the most trade with the US.

[Table 3 about here]

One also can observe that the estimated coefficients on the uninteracted trade exposure term and the two interaction terms between trade exposure and the 2012 and 2014 dummies are much smaller in terms of magnitude and none of them are statistically significantly different from zero. The dynamic estimates are visualized in Figure 5, with the red (green) line corresponding to estimates in column 2 (4) of Table 3. This lends strong support to the identifying assumption of the difference-in-differences research design, suggesting that the difference in pretreatment trends among cities with differential levels of US-specific trade exposure are not significant.

[Figure 5 about here]

In columns 5-7 of Table 3, I report the results for the effects of the trade war on Chinese people's nationalistic sentiment, obtained from estimating Equation (4) using repeated cross-section data. Note that the trade exposure variable now varies by province and by year. As before, column 5 only includes provincial and time fixed effects, column 6 further controls for individual characteristics (gender dummy, age dummies, and education-level dummies) and log provincial GDP per capita, and column 7 replaces educational-level dummies with education-year dummies. We see that columns 6 and 7 have somewhat larger estimates than column 5, both of which are large and statistically significant at the 1% level. Again, focusing attention on the parsimonious specification in column 4 and the estimated coefficient on the interaction term between trade exposure and the 2018 dummy, a one standard deviation increase in provincial-level US-specific trade exposure is associated with a 0.12 standard deviation increase in nationalism in China. Moreover, the effect magnitude accounts for about 44% of the standard deviation of nationalism for a province with trade

[26] See Panel A of Appendix Table A3 for the distribution.

exposure in 2017 equal to the 90th percentile of the distribution of the provincial trade exposure measure (e.g., Zhejiang Province).[27]

I next report the results obtained from regressions using the export tariff measure as the treatment variable in Table 4. Columns 1-4 present the results of the effects on trust in Americans obtained by estimating Equation (5) using individual-level panel data. Columns 1 and 2 report results obtained from regressions without and with individual- and city-level controls. Both control for individual and time fixed effects. Column 3 includes education-year dummies and column 4 uses a balanced panel. The estimated effects are almost identical and statistically significantly different from zero across columns. In the data, on average the city-level export tariff changes from 0.0285 in 2017 to 0.0878 in 2018. If we use this change to evaluate the effect magnitude, then it amounts to slightly more than 2% of the standard deviation of trust in Americans. The effect size is associated with a nearly 0.07 standard deviation decrease in trust in Americans for a city with the change export tariff from 2017 to 2018 ranked at 90th percentile (e.g., Shaoxin City).[28] Again, for Dongguan City, the effect magnitude is more remarkable, amounting to about 17% of the standard deviation of trust in Americans.

[Table 4 about here]

Columns 5-7 of Table 4 present the results on the effects of the trade war on nationalism obtained from estimating Equation (6) using repeated cross-section data. Again, I first report results from a regression with only provincial and time fixed effects controlled for (column 5), and then the results from a regression further augmented with individual- and provincial-level controls (column 6); column 7 replaces education-level dummies with education-year dummies. While the latter two columns yield larger estimates, all of them are statistically significantly different from zero. The data shows that the average provincial-level export tariff measure is 0.0229 in 2017 and 0.0796 in 2018, respectively, resulting in a 0.0567 difference between these two years. Focusing on column 5, this difference is associated with a 0.11 standard deviation increase in nationalism in China. The effect magnitude is equivalent to about 28% of a standard deviation of nationalism in China for a province with a difference in export tariff between 2017 and 2018 ranked at the 90th percentile (e.g., Tianjin Municipality).[29]

In summary, two insights emerge from the baseline results. First, the two baseline empirical strategies yield similar estimates of the effects of the US-China trade war on trust and nationalism both qualitatively and quantitatively, although they measure the trade war shock in different ways. Second, the effect magnitudes are economically sizable, especially for those regions more heavily exposed to trade with the US and thus affected more by the US-China trade war. Overall, the baseline results confirm that the US-China trade war had a larger impact on trust and nationalism in regions with a higher level of trade with the US, suggesting a convergence in trust or nationalism (see Appendix Figure A6).

[27] See Panel B of Appendix Table A3 for the distribution. Moreover, only three provinces had a higher level of trade exposure in 2017 than Zhejiang Province in the sample.

[28] See Panel C of Appendix Table A3 for the distribution. Guangzhou City ranks right above Shaoxin City.

[29] See Panel D of Appendix Table A3 for the distribution. There are only three provinces/municipalities ranked above Tianjin, which include Zhejiang, Guangdong, and Shanghai.

5.3 Long-Run Effects on Trust

As mentioned above, since most respondents were surveyed in the summer of 2018 (a few months after the trade war was announced) for the CFPS and WVS, my baseline results identify the short-term effects of the US-China trade war. One may wonder about the extent to which the effects are persistent. While the WVS has not done a new wave of survey in China since 2018, the CFPS conducted one wave of survey in 2020, enabling me to investigate the long-term impacts of the trade war on Chinese citizens' trust in Americans. To this end, I re-estimate Equation (3) by adding an additional interaction between the trade exposure measure and the 2020 dummy. In the regressions, I use the trade exposure variable measured in 2010 and control for individual and time fixed effects.

[Figure 6 about here]

The estimated coefficients and corresponding 95% confidence intervals are plotted in Figure 6, and the corresponding regression results are present in Appendix Table A5. The results are robust to using a balanced panel (see the green dotted line), alleviating the concern that the sample composition changes may lead to biased estimates. We can see that the effect size in 2020 is about three times larger than that in 2018. In other words, compared to those in low-trade cities, individuals in cities with more ex ante trade with the US hold a more and more negative attitude toward the US over time ever since the trade war was launched. It is worth pointing out that one should be cautious in interpreting this result, given that US-China conflicts have later on extended beyond trade to other domains such as US's aggressive criticism on China's human rights as well as US's assertive blame of the COVID-19 breakout on the Chinese government. That is to say, this much larger long-run impact may also reflect Chinese citizens' response to other US-China conflicts in addition to the trade war.

5.4 Effects of the Import Tariffs

Thus far, I have considered US tariffs on Chinese exports to construct the trade shock measure, so one may wonder whether there are any impacts of Chinese tariffs on US exports. On the one hand, higher import tariffs may raise living costs for residents by increasing consumption prices, and may intermediate input costs for firms. In this regard, increased import tariffs could be a negative shock. On the other hand, higher prices could help domestic producers of those goods benefit local residents by providing job opportunities and higher salaries. From this perspective, increased import tariffs could be a positive economic shock. So it is not clear how retaliatory import tariffs affect a certain region's economic interests. In addition to economic reasoning, increased import tariffs also may lead Chinese citizens to pay more attention to information critical of the US which in turn has impacts on trust and nationalism. Taken together, how import tariffs affect trust and nationalism is an empirical question.

[Table 5 about here]

To answer this question, I re-estimate Equations (5) and (6), replacing the export tariff measures with import tariff measures constructed using the same approach as in Equation (2). Table 5 reports the regression results. One can see that the import tariff measure has negative effects on trust in

Americans (columns 1-2), but it is not statistically significantly different from zero after individual- and city-level controls are included (column 2). Moreover, it also has positive effects on nationalism (columns 5-6), which are statistically significantly different from zero across both specifications. In terms of magnitudes, the effect sizes are similar to the effects of the export tariff measure if one evaluates them using the change in the import tariff measure from 2017 to 2018. However, when I put export and import tariff measures together in the regressions, the estimated coefficients on import tariff measure are not statistically significant for the trust regressions (columns 3-4), and none of the estimated coefficients are statistically significant for the nationalism regressions (columns 7-8). The latter result is not surprising, given that export and import tariff measures are highly correlated, especially for the provincial-level measures (Pearson's correlation coefficient > 0.8). Overall, the results suggest that the import tariffs are not important compared to export tariffs. In what follows, I thus use only export tariff measures.

5.5 Time-Invariant Trade Exposure Measure and Placebo Outcomes

In this subsection, I provide two sets of robustness checks. First, because trade itself could create trust (e.g., Rohner et al., 2013), and weaken nationalism (e.g., Lan and Li, 2015), one may worry that the baseline results, obtained from using time-varying trade exposure measure as treatment, are driven by changes in trade exposure over time so do not solely reflect the effects of trade war shocks. This is particularly concerning given that trade exposure is lower in 2017 than in 2010 (see Figure 3). To address this concern, instead of using a time-varying US-specific trade exposure measure, I use a time-invariant one only measured in 2010 and thus determined at the start of the period covered by the CFPS and WVS. I re-estimate Equations (3) and (4) without the main term because now it is time-invariant and controlled for by the region fixed effects. The estimated effects are presented in Table 6. They are largely similar to the baseline results. Taken together, the evidence suggests that the baseline empirical strategy using the time-varying measure as treatment credibly identifies the effects of trade war shocks on trust and nationalism.

[Table 6 about here]

Second, I provide a set of placebo tests for the results of effects on trust in Americans, using trust in strangers (from the CFPS) and trust in foreigners (from the WVS) as placebo outcomes. In general, regions trading a lot with others may foster a culture of trust, making people in those regions tend to be trusting of others such as strangers and foreigners. The reduction in trust due to the US-China trade war should only be applicable to Americans but not to foreigners or strangers. To test this, I re-estimate Equations (3) and (5) by replacing trust in Americans with trust in strangers, and Equations (4) and (6) by replacing nationalism with trust in foreigners. Table 7 reports the regression results. None of the regressions yield an estimate that is statistically significantly different from zero. This result supports a causal interpretation of the estimated effects on trust in Americans.

[Table 7 about here]

6 Explanations

In this section, I first report the results of the greater negative impacts of the trade war on the labor market for cities hit harder by the increased tariffs. Interestingly, there is heterogeneity in the economic impacts concerning different individual characteristics, but I do not find such heterogeneous political impacts. Taken together, these results suggest that the localized political responses may be due to greater exposure to the economic consequences of the tariff shock. Then, I provide evidence that people in cities more exposed to trade with the US would search more information related to the trade war, which is likely to be presented in a nationalistic way. This result further suggests that localized political effects may be attributable to the salience of the trade war shock in harder-hit regions. Last, I use the social identity theory to provide a unified explanation for the empirical findings of this paper. It is noteworthy that (*i*) these channels are not a exhaustive list of all possible channels, (*ii*) they are not necessarily mutually exclusive, and (*iii*) the first two channels may be at work independent of one's identity.

6.1 Heterogeneous Economic Effects and Localized Political Responses

This subsection first examines the economic impacts of the trade war. Higher export tariffs affected Chinese regions differently as some of them specialize in manufacturing sector that exports to the US while others do not. There is little doubt that a city relying more on the trade with the US prior to the trade war would be hit harder economically. Specifically, I examine the effects on labor market outcomes, focusing on two indicators: *(i)* an employment dummy indicating whether one is employed or not, and *(ii)* log of annual wage income. Using the export tariff rate as the treatment variable, I re-estimate Equation (5), replacing trust with labor market outcomes. I restrict the sample to the working age population only (ages 16-64) and exclude current students, and control variables include only age dummies, education-level dummies, and city GDP per capita (logged). Table 8 presents the estimated results. I find that both employment and annual wage income are negatively affected by increases in tariffs (columns 1 and 7, respectively). Since most respondents were surveyed in July and August of 2018 (see Panel A of Appendix Figure A5), one should interpret the results as short-term effects of the trade war. When evaluating the magnitudes using the average change in export tariffs between 2017 and 2018 (around 0.0593), the effect magnitudes are sizeable. For employment rate, the effect size is -2.4%, relative to a sample mean of 75% (-0.3053*0.0593/0.7540); while for annual wage income, the effect magnitude is a 9.5% decrease in wage income (-1.6174*0.0593). This result is consistent with the findings of Chor and Li (2021), who use high-frequency night lights data and conduct a grid-level analysis. Taken together, the evidence reported here confirms that regional labor markets are negatively affected by the trade war.

[Table 8 about here]

Next, I examine whether the trade war affects the labor market outcomes differentially across citizens with different characteristics. From columns 2-6 and 8-12 of Table 8, one can see that the employment of male workers, those with education below high school, those born before 1980, and those working in the manufacturing sector in 2016 were more negatively affected, while the heterogeneity on the effects on annual wage income appears to be less strong.

Interestingly, when I examine whether different exposure to trade war shocks of such groups corresponds to changes in trust in Americans or nationalism, I do not find any such heterogeneous political impacts. Table 9 shows that none of the groups defined by characteristics other than region exhibited heterogeneous effects on either trust or nationalism, corresponding to the heterogeneity in labor market impacts. Put differently, the political effects are localized.

[Table 9 about here]

Moreover, in addition to examining possible heterogeneity with respect to whether one was working in the manufacturing sector in 2016 (see columns 5 and 11 of Table 9), I further account for sector fixed effects directly. Table 10 reports the results. The CFPS data contains information on the Chinese industry code (CIC) at the 1-digit level (totally, 20 industries), enabling me to control for CIC 1-digit fixed effects (and a dummy indicating those not working in any of the 20 industries) when estimating the effects of tariffs on trust in Americans (column 1 of Table 10). Doing so compares two citizens in different cities with differential export tariff levels but in the same sector (e.g., the manufacturing sector). One can see that compared to the baseline estimate, including sector dummies barely changes the estimated effect. Using both the CFPS and WVS data, I also can create three indicator variables for public sector, private sector, and other sector.[30] In Table 10, columns 2 and 4 include these dummies as controls, while the specifications repeated in columns 3 and 5 further interact them with the export tariff measure. We find that the estimated effects are almost identical to the baseline estimates across all columns.[31] Overall, accounting for exposure to different industrial or ownership sectors flexibly dose not undermine the credibility of citizens responding to the trade war at the regional level.

[Table 10 about here]

Summing up, the results suggest that individuals' political responses to the trade war are based on the experience of people living in the same region. If it occurs at the national level, we would not observe the baseline results; and if it happens along other dimensions rather than regional trade exposure, we would not obtain the results presented in Tables 9 and 10.

6.2 Information Search Behavior

This subsection investigates the information environment in China after the trade war and people's information search behavior. I show that citizens in regions doing more trade with the US are more likely to search for information about the trade war, this could reinforce the salience of nationalistic sentiment, since state-owned media is likely to present information about the trade war in a way that

[30] Public sector includes government agencies, state-owned enterprises, and public institutions such as universities and research institutes. Private sector includes private business and industry and the self-employed. Other sector includes non-government organizations and the unemployed and so on. In the regressions, the dummy for private sector is omitted.

[31] It is not surprising that the estimated coefficients on the public sector dummy are positive and statistically significantly different from zero in columns 4-5 since public sector workers are exposed to more government propaganda in China.

is critical of the US and portray the trade war as a US attack on China. Below, I provide descriptive evidence on information search about the trade war using event study plots and conduct empirical tests of how such search is related to tariff measures.

Specifically, I draw on data obtained from Baidu. Figure 7 plots the national-level daily time series of Baidu media, search, and information-flow indices for the keywords "US-China trade war" or "trade war" for the period 2017-2018. These indices measure the frequency of news articles with titles mentioning the keywords (supply side), the search frequency of the keywords (demand side), and the information-flow of the keywords (real consumption of information), respectively (see Section 3 for detailed descriptions). From Panels A, B, and D, one can observe a prominent pattern that all the three indices surged when the US announced tariff increases on Chinese exports (late March of 2018). One may be curious about what type of information is available on Baudu for people to search. A quick search of "US-China trade war" reveals that of the 10 most popular pieces of information in 2018, more than half were provided by the Chinese state-owned media, such as the *People's Daily* and *CNR News*,[32] suggesting that government influences the content of a large share of the information available on Baidu. Taken together, these patterns suggest that anti-American sentiment is likely to have increased after Trump unilaterally launched the trade war against China.

[Figure 7 about here]

Moreover, one also can see from Panel C that the Baidu search index for Dongguan (one of the cities doing the most trade with the US) resembles the national-level trend, but the search index for Yuxi (a city that does not trade a lot with the US) tends to flatten out during the post-trade war period. This is consistent with that the demand for information pertaining to the trade war being sought more actively in cities with more trade with the US.

Table 11 presents the results obtained from estimating Equation (7). Restricting attention to column 3, three insights arise. First, cities that have an average level of access to broadband Internet will search more on Baidu if they have a higher export tariff level (positive τ). Second, for cities with an average export tariff level, gaining more access to broadband Internet does not boost their Baidu search. Third, in cities doing more trade with the US as well as having higher access to broadband Internet (than average), citizens have much more demand for information regarding the trade war compared to cities that do not (positive ρ).

[Table 11 about here]

One might worry searching for relevant information does not automatically translate into consuming that information. To partially address this concern, using a month-city panel for the period July-December 2018, I plot the correlation between the Baidu search and information-flow indices in Figure 8, in which the latter reflects Baidu users' real consumption behavior of news, posts, and reports about the trade war. Notice that the two indices are constructed independently. Figure 8 shows a very high correlation (regression-based R-squared = 0.89), suggesting that people do consume the information they get from Baidu.

[Figure 8 about here]

[32]See: https://bit.ly/37Sp9pP. Last access on August 17, 2021.

Taken together, the results suggest that Chinese cities exposed to higher trade with the US and thus to larger trade war shocks paid more attention to relevant information about the trade war. The greater attention paid to such information, much of it provided by state-owned media, would be expected to make the trade war more salient to them and thus lead to more negative political responses.

6.3 Social Identity Theory: A Unified Explanation

I now turn to provide a unified explanation for the above-documented empirical findings by using a simple model of trade and identity, adapting a theoretical framework first proposed by Shayo (2009) and used recently in application to trade (Grossman and Helpman, 2021).[33] Here I only briefly describe the model and relegate the detail of the model in Appendix B. The model considers a 2 × 2 setting: two regions with different degrees of trade penetration (high versus low) and two social identities (US-friendly versus nationalistic), in which regions are associated with types of individuals in society.[34] The model provides a framework for understanding how citizens in different regions choose their social identities before and after the US-China trade war.

How does one choose her social identity? One identifies with the group that gives her a higher utility under given circumstances. In my setting, in addition to individual material payoffs, individuals also derive utility from the social identification process, which consists of two components: *(i)* a perceived utility gain from being part of group that enjoys higher economic status, and *(ii)* a utility loss from the distance between herself and the average group member along important dimensions.

An important assumption of the model is that a person's perception of group status is based on the experiences of people living in her own region, which is observable to her. Thus, individuals living in cities or provinces with greater trade exposure associate a higher group status for being US-friendly. This assumption implies that social identity choices reflect local group payoffs. One may worry that in evaluating the status of different social groups, individuals may not focus on the experiences of those living in the same region, but rather assess the experiences of peer groups defined by other characteristics, for example individuals working in the same sector. The results reported in Tables 8, 9 and 10 are supportive of citizens choosing their social identities based on the experiences of those living in the same region rather than the experiences of groups defined by other characteristics.

The trade war affects both group economic status and perceived distance in the following ways. First, group status is mainly determined by an average member's material payoffs in the model. Prior to the trade war, citizens who identify with the US-friendly group have a higher group status, because they are exposed more to the trade with the US and thus enjoy larger material payoffs. Since the trade war occurred mainly through increased tariffs imposed by both sides on each other's exports, it creates a negative economic shock, especially to workers in high-trade regions. Consequently, a

[33]For earlier studies on social identity theory and its variant self-categorization theory in social sciences, see, for example, Tajfel (1974), Tajfel and Turner (1979), Tajfel (1981), Turner (1985), and Stryker and Burke (2000).

[34]Although this paper restricts attention to the US-China trade relationship and thus only to an US-friendly identity among Chinese citizens, one can view this US-friendly identity as one dimension of a globalized identity and can easily extend the analysis to a more general context. For example, Besley and Persson (2021) who consider cosmopolitan versus nationalistic identities.

reduction in group status lead fewer citizens in high-trade regions to identify with the US-friendly group.

Second, the perceived distance captures whether one is similar to the average member along prominent attributes and/or whether one conforms to prescribed group behaviors or norms.[35] In general, which behaviors or norms are more salient in society can largely influence one's identity choice.[36] In my framework, before the trade war, citizens in different regions choose identities along the dimension of trade penetration from the US.[37] At this stage, citizens do not link US-friendly behaviors like buying US goods to one's loyalty to China. However, the trade war awakens the salience of national identity, shifting Chinese citizens' attention toward the common threat from the US and putting social pressure on all citizens to behave nationalistically. In this case, because nationalistic actions resume suppression of US-friendly attributes, it increases the distance with expected behaviors of those who are US-friendly. Hence, citizens eventually tend to align with the Chinese nation.

Mapping the theory to the empirics, I treat being friendly to the US as having more trust in Americans and aligning with the Chinese nation as being more nationalistic. In the literature (both theoretical analyses and evidence from experiments and the field), trust often is strongly associated with identity, for example being of the same race, ethnicity, or nationality (Glaeser, Laibson, Scheinkman and Soutter, 2000; Fershtman and Gneezy, 2001; Tanis and Postmes, 2005; Basu, 2010; Falk and Zehnder, 2013, among others). In this regard, US-friendly can be interpreted as US-trusting.

Taken together, the theory delivers two clear predictions. First, before the trade war, citizens in regions penetrated more by the trade with the US are more likely to be US-friendly. Both regression-based evidence (see Table 2) and empirical pattern observed from the data (see Figure 9) confirm that prior to the trade war, Chinese citizens exposed more to trade with the US had more trust in Americans and were less nationalistic compared to those with a lower level of trade exposure, consistent with the literature on the positive (negative) relationship between trade and trust (nationalism) (e.g., Rohner et al., 2013; Lan and Li, 2015). This result suggests that common experience occurred at the regional level (a more international environment in my research setting) helps shape a regional identity (a US-friendly identity or globalist), in line with the findings of Dehdari and Gehring (2022).

[Figure 9 about here]

Second, after the US-China trade war, citizens in regions doing more trade with the US are more likely to switch their identity to the nationalistic group (see Section 5.2), through the two independent social identification channels discussed above: lower group status due to larger negative labor market shocks (see Section 6.1) and greater perceived distance because of more salient membership (see Section 6.2). These findings are consistent with the literature on how external threats or shared

[35] See Bénabou and Tirole (2011), Bursztyn, Callen, Ferman, Gulzar, Hasanain and Yuchtman (2020), and Jia and Persson (2021) for how social norms matter for choosing identity.

[36] See, for example, Benjamin, Choi and Strickland (2010) and Bonomi et al. (2021). Also, see Bordalo, Gennaioli and Shleifer (2022) for a survey of the fast-growing literature on salience in economics with theoretical analysis.

[37] A representative high-trade (low-trade) citizen bears a utility loss only when she chooses a national (US-friendly) identity and/or behaves in a US-friendly (nationalistic) way.

nationwide experiences could foster a national identity or nation-building more broadly (e.g., Dell and Querubin, 2018; Depetris-Chauvin et al., 2020), or even an identity with membership going beyond the national level, such as a European Union identity (Gehring, 2022).

6.4 Further Discussion

Several final remarks are in order. First and admittedly, greater exposure to negative economic impacts or salience of the trade war shock could affect one's political attitudes and beliefs independent of one's identity, but they also may influence one's political responses through social identification. Empirically, it is hard to completely differentiate the two channels from the identity channel. Nevertheless, the fact that different individual characteristics lead to heterogeneous effects on labor market outcomes but not on political outcomes makes the social identity framework a plausible explanation. Importantly, the purpose of presenting a social identity framework in this paper is to help readers better understand the empirical findings from a theoretical perspective, which offers useful insights and important implications.

Second, it is also worth emphasizing that the two identity-based channels can be interrelated in a manner that adverse economic shocks shape the sociopolitical environment (e.g., see Autor et al., 2020; Bonomi et al., 2021; Rodrik, 2021). Indeed, we do observe that people in regions affected more by the tariffs search more information about the trade war and thus are likely more exposed to an information environment critical of the US.

Third, the localized political impacts may also be due to differential levels of local government propaganda across regions. However, this is not the case as evidenced by Fan et al. (2022) who use an empirical strategy similar to Equation (5) to estimate the impacts of the Trump tariffs on the number of local articles with titles mentioning the trade war and find no statistically significant results. As they noted, this is likely due to the fact that the Chinese government directed official media to play down the trade war.

Fourth, for the main baseline findings, there could exist alternative channels. For example, the sudden disruption to the US-China trade, which was unilaterally lunched by Trump and illy justified, may directly damage trade reputation of the US. Although some of these pathways can partially be captured by the perceived distance channel, the results presented above are not enough to completely rule out these possibilities.

7 Concluding Remarks

The US-China trade war that began in 2018 has been one of the world's most influential political events in recent years, profoundly reshaping the global economy and politics and putting the world again in a situation similar to the Cold War. By incorporating bilateral trade into social identity theory, this paper offers a theoretical framework to better understand how the trade war affects social identity choices that reshape political attitudes toward the US and China. The empirical results reveal that after Trump launched the trade war in the beginning of 2018, it had a larger negative impact on trust in Americans for Chinese citizens living in regions with a higher level of ex ante US trade exposure, and a larger positive impact on nationalistic sentiment, consistent with the theory. I also find evidence that the trade war creates a negative shock to labor market outcomes in regions with more ex ante trade with the US, reducing the economic status of US-friendly citizens, and that it is likely that after the trade war nationalistic sentiment was made more salient in the information environment, which pushed high-trade citizens become more nationalistic. Both channels can lead to a reduction in trust in Americans and a rise in nationalism.

As a prominent example of trade deliberalization (or deglobalization more broadly), the political economy consequences of the US-China trade war have important implications. The existing literature has found that the distributional consequences of trade liberalization have brought about adverse political impacts across a number of countries around the world. This appears to also be true in the case of trade deliberalization based on the findings of this paper. Similar to the Cold War, the political implications of the trade war should be of concern to policymakers and government leaders. The intensity and persistence of the trade war and its negative political consequences could be self-reinforcing, leading to longer term erosion of trust that could have lasting political and economic consequences.

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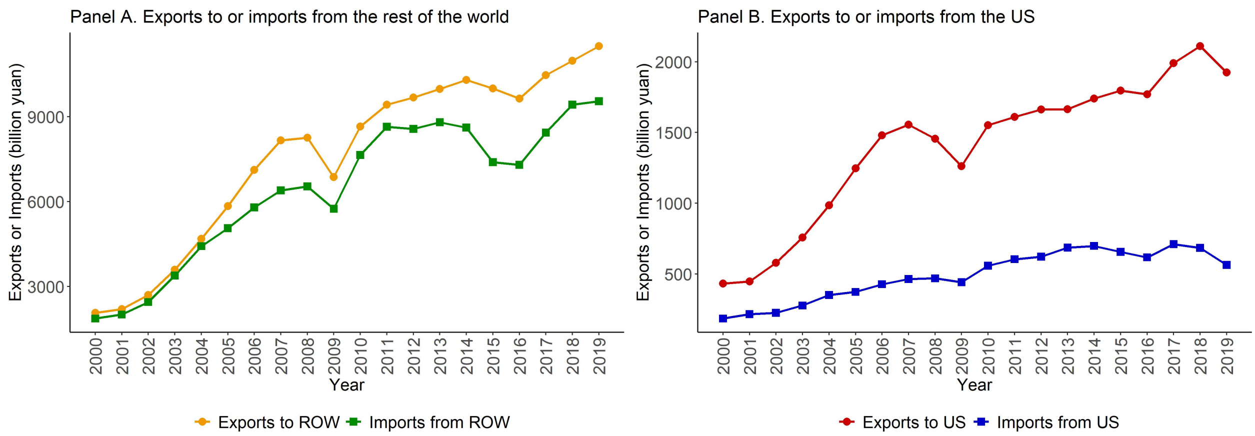


Figure 1: China's Exports and Imports

Notes: Panels A and B plot China's exports to and imports from the rest of the world (including the US) and the US (in 2000 yuan), respectively.

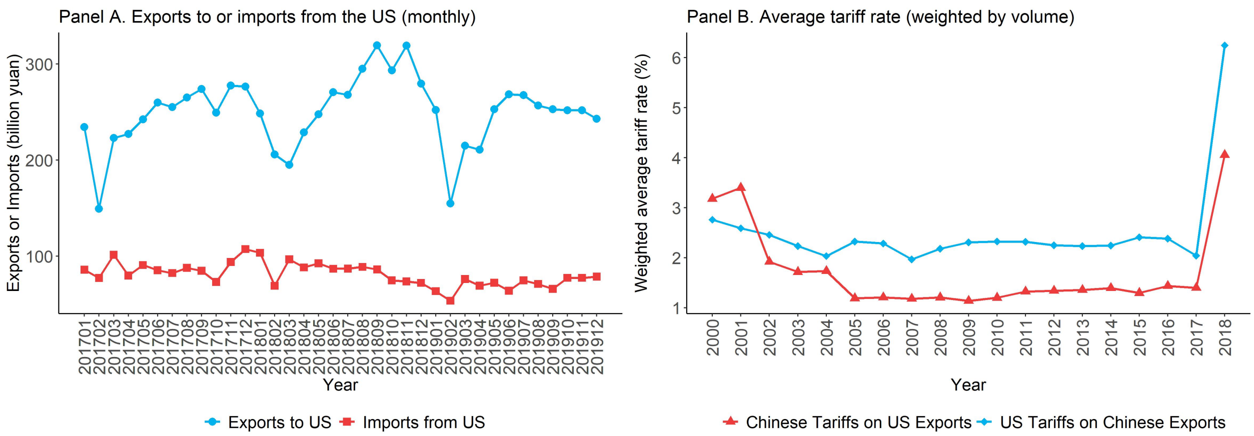


Figure 2: Exports, Imports, and Tariffs Between China and the US

Notes: Panel Aplots China's exports to and imports from the US during 2017-2019; Panel B plots weighted (by volume) average tariff rate of Chinese exports to the US and imports from the US across all HS 8-digit levels.

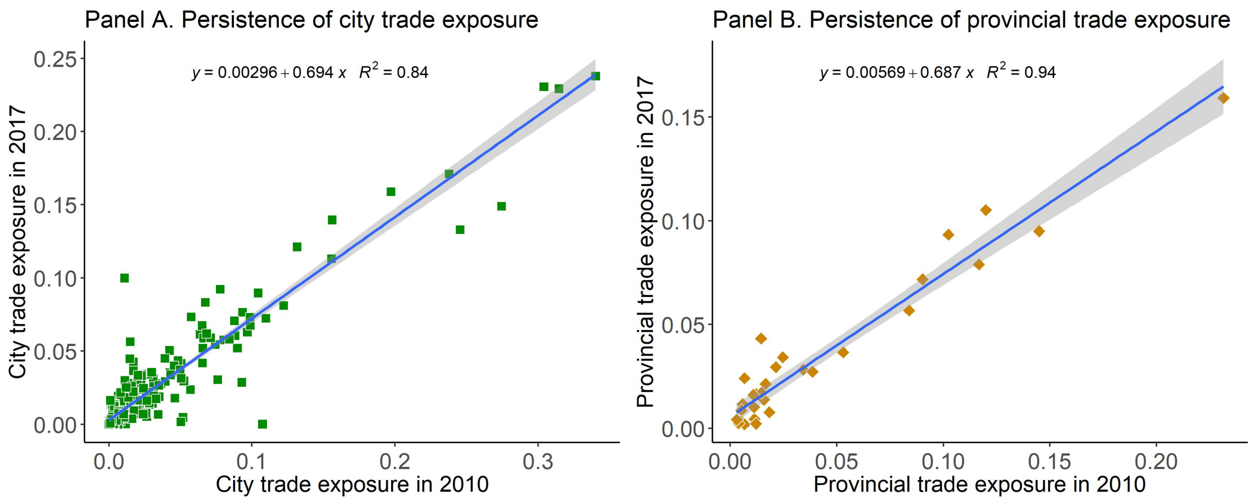


Figure 3: Persistence of US-Specific Trade Exposure from 2010 to 2017

Notes: The data sources are China's General Administration of Customs. Panels A and B plot the 2010 trade exposure measure against the 2017 one at the city- and provincial-level, respectively.

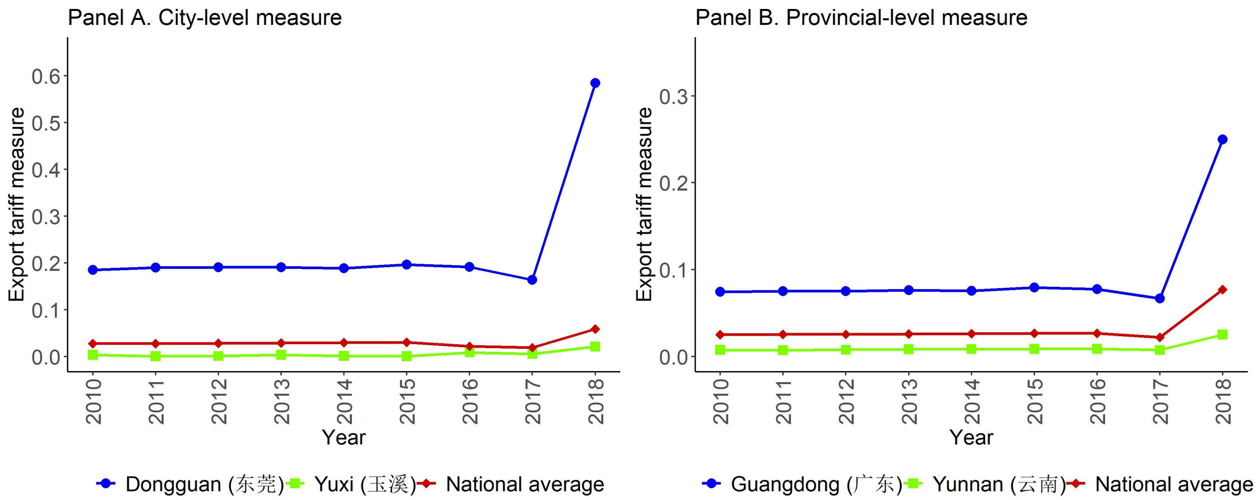


Figure 4: Export Tariff Measure

Notes: Panels A and B plot city- and provincial-level export tariff measures, respectively.

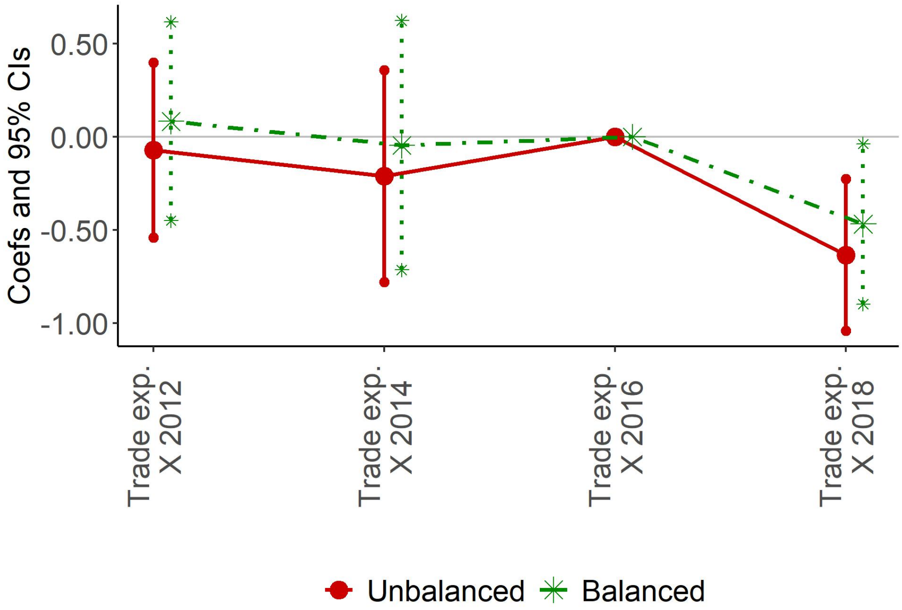


Figure 5: Visualization of Dynamic Effects on Trust in Americans

Notes: This figure plots coefficients and 95% confidence intervals of interaction terms between trade exposure (t-1) and the time dummies. The red solid (green dashed) line uses estimates obtained from an unbalanced (balanced) panel.

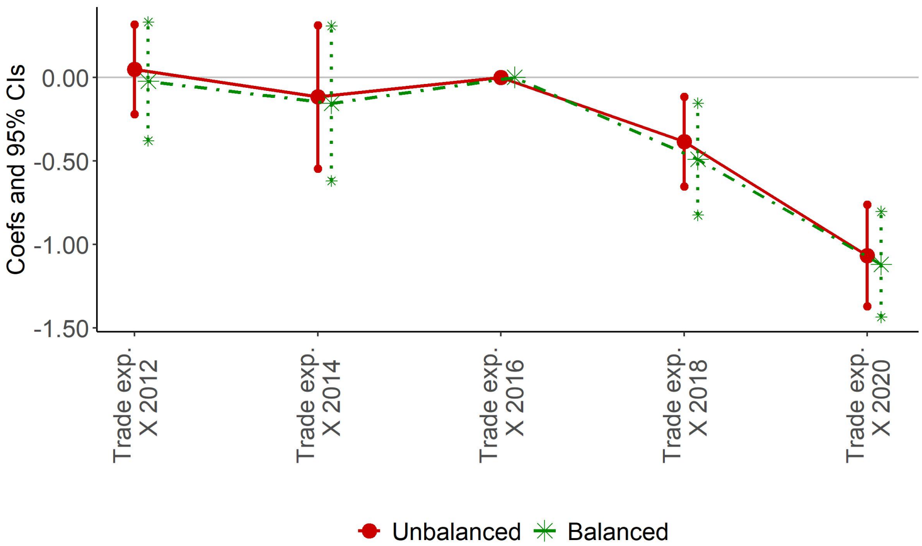


Figure 6: Long-Run Effects on Trust in Americans

Notes: This figure plots coefficients and 95% confidence intervals of interaction terms between trade exposure (2010) and the time dummies (including the 2020 dummy). The red solid (green dashed) line uses estimates obtained from an unbalanced (balanced) panel.

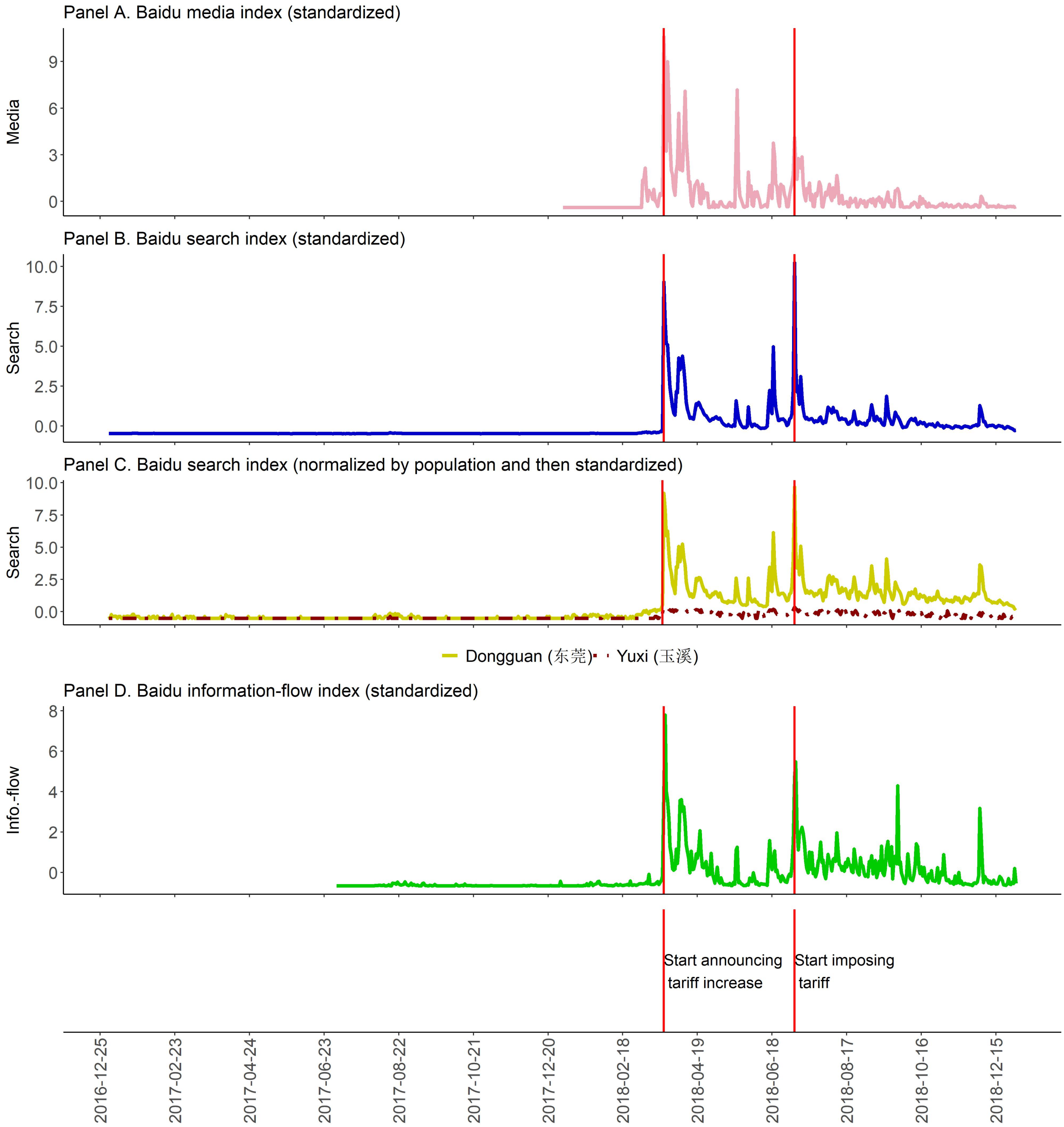


Figure 7: Baidu Indices

Notes: Panels A, B, and D plot national-level Baidu media, search, and information-flow indices, respectively. Panel C plots Baidu search index for Dongguan (solid line) and Yuxi (dashed line). Dongguan (Yuxi) has a high (low) exposure to the trade with the US.

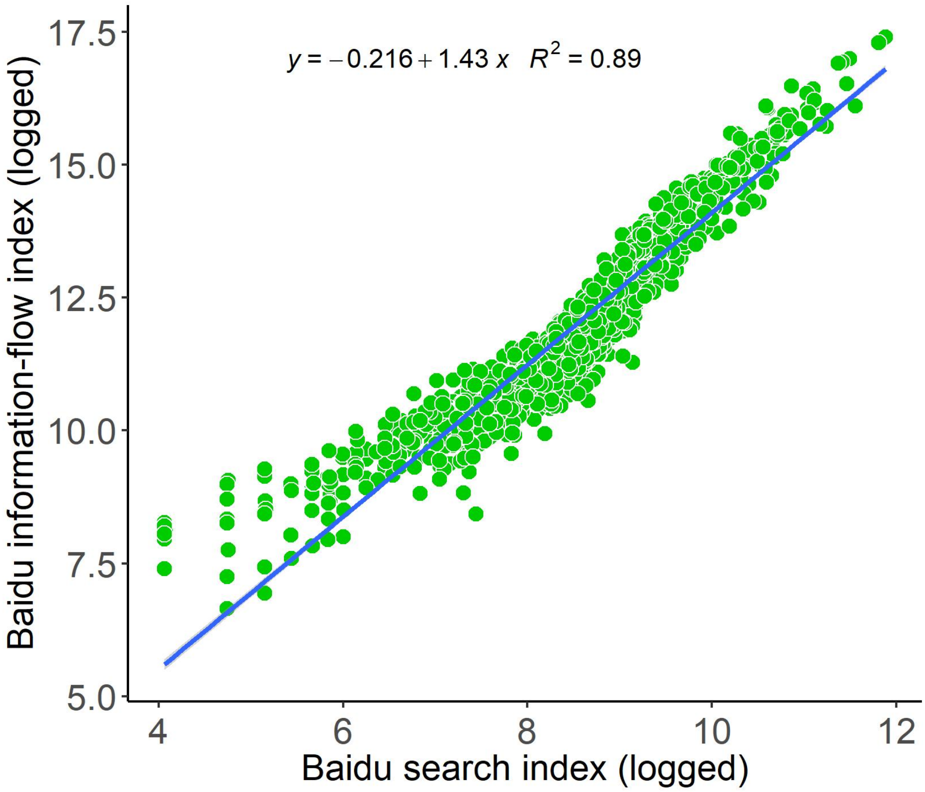


Figure 8: Correlation between Baidu Search and Information-flow Indices

Notes: This figure plots the correlation between Baidu search and information-flow indices, using city-month panel data spanning from July to December 2018 for around 280 Chinese cities.

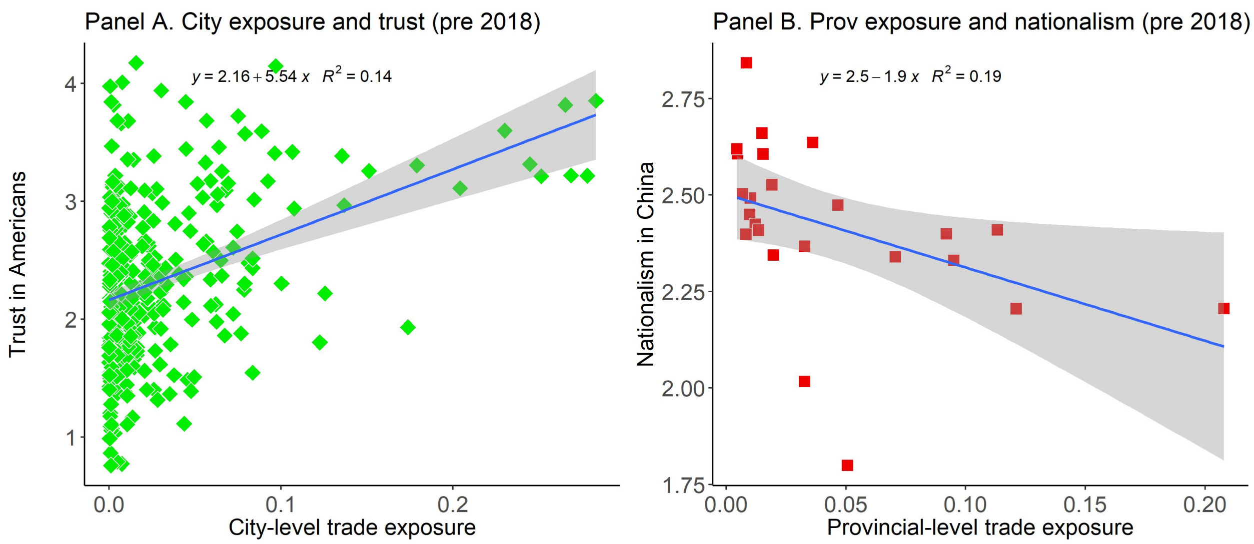


Figure 9: Correlation between Trade Exposure and Trust in Americans/Nationalism in China

Notes: Panels A and B plot the lagged trade exposure against trust in Americans (city averages using data excluding the 2018 wave of the CFPS) and nationalism in China (provincial averages using data excluding the 2018 wave of the WVS), respectively.

Table 1: Summary Statistics for Key Variables

	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
Panel A. Trade war shock measures					
City trade exposure: 2010-2017	2269	0.0225	0.0407	0	0.3403
City trade exposure: 2010	280	0.0258	0.0493	0	0.3403
City trade exposure: 2017	285	0.0205	0.0355	0	0.2378
Provincial trade exposure: 2010-2017	248	0.0368	0.0446	0.0019	0.2315
Provincial trade exposure: 2010	31	0.0401	0.0539	0.0030	0.2315
Provincial trade exposure: 2017	31	0.0332	0.0382	0.0019	0.1591
City export tariff: 2010-2018	2794	0.0361	0.0563	0	0.6226
City export tariff: 2017	292	0.0285	0.0381	0	0.2409
City export tariff: 2018	291	0.0878	0.1138	0	0.6226
Provincial export tariff: 2010-2018	279	0.0316	0.0377	0	0.2703
Provincial export tariff: 2017	31	0.0229	0.0224	0	0.1030
Provincial export tariff: 2018	31	0.0796	0.0743	0.0004	0.2703
City import tariff: 2010-2018	2563	0.0511	0.0800	0	0.7427
City import tariff: 2017	273	0.0439	0.0553	0	0.2482
City import tariff: 2018	272	0.1329	0.1641	0	0.7427
Provincial import tariff: 2010-2018	279	0.0599	0.0644	0	0.5713
Provincial import tariff: 2017	31	0.0502	0.0419	0.0020	0.1954
Provincial import tariff: 2018	31	0.1514	0.1253	0.0047	0.5713
Panel B. Baseline outcomes					
Trust in Americans	122564	2.4214	2.5183	0	10
Nationalism in China	4854	2.6345	0.5528	0.5692	3.5169
Panel C. Labor market outcomes					
Employment dummy	87646	0.7514	0.4322	0	1
Log annual wage income	48940	7.3062	4.3285	0	16.1477
Panel D. Baidu search index					
City Baidu search per capita: 2011-2018	2330	0.0029	0.0085	0	0.0850
City Baidu search per capita: 2017	292	0.0002	0.0002	0	0.0011
City Baidu search per capita: 2018	292	0.0226	0.0113	0.0047	0.0850

Notes: In Panel A, trade exposure and export tariff measures are constructed from using Equations (1) and (2), respectively. Import tariff measures are constructed from using an equation analogous to Equation (2). Data on trade exposure, export/import tariff measures is a city-year panel spanning from 2010 to 2017 (2018). Data sources are China's General Administration of Customs, China's 2010 Population Census, the Chinese City and Provincial Statistical Yearbooks, the World Integrated Trade Solution (https://wits.worldbank.org/), the Office of the United States Trade Representative (https://ustr.gov/), and the Tariff Bureau of the Ministry of Finance of the People's Republic of China (http://gss.mof.gov.cn/). In Panel B, trust in Americans is a categorical variable, ranging from 0 (extremely low trust) to 10 (extremely high trust), with data obtained from the China Family Panel Studies which is a four-year (2012, 2014, 2016, and 2018) individual-level panel; nationalism in China is an index calculated from a principal component analysis using three variables measuring different dimensions of nationalism, with data obtained from the World Values Survey which is a two-year (2013 and 2018) repeated cross-section. In Panel C, employment dummy indicates whether one is employed or not when surveyed, annual wage income is the total income earned from all jobs taken by the respondent in the past 12 months. Data on both variables is obtained from the China Family Panel Studies. The sample is restricted to the working age population only (ages 16-64) and excludes current students. In Panel D, Baidu search index measures the frequency of searching the keywords of *"US-China trade war" or "trade war"* (Chinese: *"Zhongmei Maoyizhan" or "Maoyizhan"*), weighted by population, with data obtained from the Baidu Index (https://index.baidu.com/) which is a city-year panel spanning from 2011 to 2018. Refer to this table for data sources and variable definitions in this paper.

Table 2: Effects of Trade Exposure on Trust and Nationalism: Before the Trade War

	Trust in Americans		Nationalism in China	
	(1)	(2)	(3)	(4)
Trade exposure (t-1)	2.2357***	2.0484***	−3.7689***	−9.6101***
	(0.1709)	(0.2219)	(0.8189)	(2.0634)
Log GDP per capita		−0.0030		0.6209***
		(0.0364)		(0.1875)
Trade exposure level	City	City	Province	Province
Num. clu.	114	114	24	24
Num. obs.	82846	82001	1886	1886
R-sq.	0.0201	0.0733	0.0231	0.0995
Time FEs	Yes	Yes		
Control variables		Yes		Yes

Notes: Unit of observation is the individual-year. The sample is a three-year panel (2012, 2014, and 2016) for columns 1-2, and a one-year cross-section (2013) for columns 3-4. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Trade exposure is the sum of exports to and imports from the US divided by GDP in the previous year. Control variables include gender dummy, age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-2, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 3-4. Robust standard errors in parentheses, clustered at the city and province level for columns 1-2 and 3-4, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 3: Effects on Trust and Nationalism: US-Specific Trade Exposure (lagged)

	Trust in Americans				Nationalism in China		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trade exposure (t-1)	−0.0657	0.0829	0.1265	−0.1099	0.5764	0.9301	0.6677
	(0.4804)	(0.5148)	(0.5122)	(0.6077)	(3.7144)	(3.4370)	(3.3423)
Trade exposure (t-1) X 2012	−0.0048	−0.0716	−0.1445	0.0829			
	(0.2251)	(0.2400)	(0.2356)	(0.2720)			
Trade exposure (t-1) X 2014	−0.1475	−0.2116	−0.2194	−0.0456			
	(0.2935)	(0.2903)	(0.2771)	(0.3416)			
Trade exposure (t-1) X 2018	−0.6878***	−0.6345***	−0.5758***	−0.4687**	4.7543***	5.5956***	5.6799***
	(0.1939)	(0.2084)	(0.2121)	(0.2194)	(1.4205)	(1.3063)	(1.3085)
Log GDP per capita		−0.0674	−0.0765	−0.0426		−0.1696	−0.1606
		(0.0590)	(0.0587)	(0.0594)		(0.4816)	(0.4809)
Trade exposure level	City	City	City	City	Province	Province	Province
Num. clu.	115	115	115	115	53	53	53
Num. obs.	108511	107668	108511	68195	4854	4829	4854
R-sq.	0.5919	0.5929	0.5936	0.5303	0.0428	0.0672	0.0689
Individual FEs	Yes	Yes	Yes	Yes			
Provincial FEs					Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables		Yes	Yes	Yes		Yes	Yes
Education FEs X year FEs			Yes				Yes
Balanced panel				Yes			

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-4, and a two-year repeated cross-section (2013 and 2018) for columns 5-7. The omitted group in the regressions is the interaction between the trade exposure variable and the 2016 (2013) dummy for columns 1-4 (5-7). The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Trade exposure is the sum of exports to and imports from the US divided by GDP in the previous year. Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-4, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 5-7. Columns 3 and 7 replace education-level dummies with education-by-year dummies. Column 4 uses a balanced panel. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-4 and 5-7, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 4: Effects on Trust and Nationalism: US Tariffs on Chinese Exports

	Trust in Americans				Nationalism in China		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export tariff	-0.3933^{***}	-0.3970^{***}	-0.3438^{***}	-0.3838^{***}	1.9867^{***}	2.6142^{***}	2.5111^{***}
	(0.1042)	(0.1163)	(0.1164)	(0.1236)	(0.6842)	(0.8303)	(0.8421)
Log GDP per capita		−0.0585	−0.0666	−0.0385		−0.2096	−0.2090
		(0.0557)	(0.0556)	(0.0561)		(0.5691)	(0.5704)
Export tariff level	City	City	City	City	Province	Province	Province
Num. clu.	126	115	115	115	53	53	53
Num. obs.	115220	106667	107497	67648	4854	4854	4829
R-sq.	0.5975	0.5955	0.5962	0.5328	0.0399	0.0655	0.0640
Individual FEs	Yes	Yes	Yes	Yes			
Provincial FEs					Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables		Yes	Yes	Yes		Yes	Yes
Education FEs X year FEs			Yes				Yes
Balanced panel				Yes			

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-4, and a two-year repeated cross-section (2013 and 2018) for columns 5-7. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Export tariff is constructed by using Equation (2). Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-4, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 5-7. Columns 3 and 7 replace education-level dummies with education-by-year dummies. Column 4 uses a balanced panel. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-4 and 5-7, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 5: Effects on Trust and Nationalism: Chinese Tariffs on US Exports

	Trust in Americans				Nationalism in China			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Export tariff			−0.8032***	−0.7486***			1.4384	2.2277
			(0.2836)	(0.2800)			(1.3643)	(1.6484)
Import tariff	−0.1528*	−0.1214	0.2590	0.2561	1.2993**	1.5193***	0.4327	0.2120
	(0.0814)	(0.0884)	(0.1821)	(0.1817)	(0.5349)	(0.5593)	(0.9723)	(0.9563)
Log GDP per capita		−0.0906		−0.0760		0.0462		−0.1817
		(0.0574)		(0.0571)		(0.5349)		(0.5999)
Tariff level	City	City	City	City	Province	Province	Province	Province
Num. clu.	122	114	122	114	53	53	53	53
Num. obs.	103488	99334	103488	99334	4854	4829	4854	4829
R-sq.	0.6145	0.6087	0.6146	0.6088	0.0397	0.0635	0.0399	0.0640
Individual FEs	Yes	Yes	Yes	Yes				
Provincial FEs					Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables		Yes		Yes		Yes		Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-4, and a two-year repeated cross-section (2013 and 2018) for columns 5-8. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Export tariff is constructed by using Equation (2). Import tariff is constructed by using an equation analogous to Equation (2). Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-2, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 3-4. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-4 and 5-8, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 6: Effects on Trust and Nationalism: US-Specific Trade Exposure (2010)

	Trust in Americans		Nationalism in China	
	(1)	(2)	(3)	(4)
Trade exposure (2010) X 2012	-0.0021	-0.0305		
	(0.1498)	(0.1572)		
Trade exposure (2010) X 2014	-0.1614	-0.1959		
	(0.2176)	(0.2057)		
Trade exposure (2010) X 2018	-0.4455^{***}	-0.4048^{***}	1.4990^{***}	1.7855^{***}
	(0.1439)	(0.1553)	(0.4663)	(0.5140)
Log GDP per capita		-0.0697		-0.0163
		(0.0566)		(0.5378)
Trade exposure level	City	City	Province	Province
Num. clu.	115	115	53	53
Num. obs.	108511	107668	4854	4829
R-sq.	0.5919	0.5929	0.0405	0.0646
Individual FEs	Yes	Yes		
Provincial FEs			Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Control variables		Yes		Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-2, and a two-year repeated cross-section (2013 and 2018) for columns 3-4. The omitted group in the regressions is the interaction between the trade exposure variable and the 2016 (2013) dummy for columns 1-2 (3-4). The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Trade exposure is the sum of exports to and imports from the US divided by GDP in 2010 year. Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-2, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 3-4. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-2 and 3-4, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 7: Effects on Trust in Strangers or Foreigners: Placebo Test

	Trust in strangers		Trust in foreigners	
	(1)	(2)	(3)	(4)
Trade exposure (t-1)	−0.4331		7.8101	
	(0.5516)		(6.4852)	
Trade exposure (t-1) X 2012	−0.0076			
	(0.2677)			
Trade exposure (t-1) X 2014	0.0578			
	(0.2396)			
Trade exposure (t-1) X 2018	−0.1713		0.8721	
	(0.2999)		(1.7993)	
Export tariff		−0.0425		−1.1475
		(0.1692)		(1.2699)
Log GDP per capita	−0.0785	−0.0923	−0.2802	−0.1024
	(0.0773)	(0.0705)	(0.4598)	(0.4898)
Trade/tariff level	City	City	Province	Province
Num. clu.	115	115	53	53
Num. obs.	109928	108920	4157	4157
R-sq.	0.5685	0.5716	0.0724	0.0722
Individual FEs	Yes	Yes		
Provincial FEs			Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-2, and a two-year repeated cross-section (2013 and 2018) for columns 3-4. The outcomes are standardized (mean=0, SD=1); trust in strangers/foreigners is a categorical variable ranging from 0/1 (extremely low trust) to 10/4 (extremely high trust). Export tariff is constructed by using Equation (2). Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-2, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 3-4. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-2 and 3-4, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 8: Effects on Labor Market Outcomes: US Tariffs on Chinese Exports

	Employment dummy						Log annual wage income					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Export tariff	-0.3035^{**}	-0.2152^{*}	-0.2338^{*}	-0.4141^{***}	-0.2628^{**}	-0.1938	-1.6174^{*}	-0.5182	-0.6450	-1.8058^{*}	-1.0305	0.8611
	(0.1288)	(0.1281)	(0.1233)	(0.1342)	(0.1314)	(0.1340)	(0.9454)	(1.2880)	(1.2448)	(0.9622)	(1.1061)	(1.9111)
Export tariff X male		-0.1504^{***}				-0.1443^{***}		-2.0425^{*}				-2.0779
		(0.0469)				(0.0515)		(1.1769)				(1.3303)
Export tariff X >=high school			-0.1582^{*}			-0.3038^{***}			-1.8520^{*}			-2.5704^{*}
			(0.0842)			(0.0922)			(1.0740)			(1.3384)
Export tariff X >=1980				0.3310^{***}		0.4975^{***}				0.4609		1.6471
				(0.0849)		(0.1080)				(0.8002)		(1.1394)
Export tariff X manufacturing (2016)					-0.1461^{***}	-0.1705^{***}					-1.6099^{**}	-1.8745^{*}
					(0.0508)	(0.0578)					(0.8186)	(1.0743)
Log GDP per capita	0.1003^{**}	0.1002^{**}	0.0995^{**}	0.0985^{**}	0.1006^{**}	0.0973^{**}	-0.0131	-0.0071	-0.0328	-0.0146	-0.0149	-0.0423
	(0.0393)	(0.0404)	(0.0394)	(0.0394)	(0.0394)	(0.0409)	(0.3607)	(0.3631)	(0.3596)	(0.3613)	(0.3591)	(0.3603)
Dep. var. mean	0.7540	0.7515	0.7540	0.7540	0.7540	0.7515	7.3204	7.3204	7.3204	7.3203	7.3204	7.3203
Dep. var. SD	0.4307	0.4322	0.4307	0.4307	0.4307	0.4322	4.3243	4.3243	4.3243	4.3244	4.3243	4.3244
Export tariff level	City	City	City	City	City	City	City	City	City	City	City	City
Num. clu.	115	115	115	115	115	115	115	115	115	115	115	115
Num. obs.	84962	84109	84962	84954	84962	84101	47544	47544	47544	47542	47544	47542
R-sq.	0.6388	0.6404	0.6388	0.6389	0.6388	0.6408	0.8668	0.8669	0.8669	0.8668	0.8669	0.8670
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018). The sample excludes those who are students when surveyed, and is further restricted to the working-age population (ages 16-64). Employment dummy indicates whether the respondent is employed or not when surveyed; annual wage income is calculated from various self-reported incomes for jobs that the respondent has taken in the past 12 months (logged). Export tariff is constructed by using Equation (2). Control variables include age dummies, education-level dummies, and city GDP per capita (logged). Four possible sources of heterogeneity are examined: male vs. female; education (>= vs. < high-school); birth cohort (>= vs. < 1980); and whether one was working in manufacturing sector in 2016 when surveyed. Robust standard errors in parentheses, clustered at the city level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 9: Heterogeneous Effects on Trust and Nationalism: US Tariffs on Chinese Exports

	Trust in Americans					Nationalism in China			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export tariff	-0.3978^{***}	-0.3547^{***}	-0.4387^{***}	-0.4500^{***}	-0.4419^{***}	2.3568^{***}	2.3757^{***}	2.5912^{***}	2.5546^{***}
	(0.1301)	(0.1325)	(0.1424)	(0.1390)	(0.1544)	(0.8573)	(0.8815)	(0.8201)	(0.8406)
Export tariff X >=male	0.0016				−0.0004	0.0525			0.0164
	(0.1003)				(0.0962)	(0.3606)			(0.3795)
Export tariff X >=high school		−0.1011			−0.1797		0.0101		0.1378
		(0.1121)			(0.1299)		(0.3331)		(0.4260)
Export tariff X >=1980			0.1264		0.2038			−0.2698	−0.3128
			(0.2038)		(0.2426)			(0.3767)	(0.4983)
Export tariff X manufacturing (2016)				0.2538	0.2553				
				(0.3687)	(0.3716)				
Log GDP per capita	−0.0585	−0.0583	−0.0592	−0.0588	−0.0597	−0.1619	−0.1608	−0.2099	−0.2019
	(0.0557)	(0.0557)	(0.0557)	(0.0556)	(0.0554)	(0.5718)	(0.5729)	(0.5704)	(0.5729)
Export tariff level	City	City	City	City	City	Province	Province	Province	Province
Num. clu.	115	115	115	115	115	53	53	53	53
Num. obs.	106667	106667	106659	106667	106659	4643	4643	4829	4829
R-sq.	0.5955	0.5955	0.5956	0.5955	0.5956	0.0627	0.0627	0.0640	0.0640
Individual FEs	Yes	Yes	Yes	Yes	Yes				
Provincial FEs						Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-5, and a two-year repeated cross-section (2013 and 2018) for columns 6-9. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Export tariff is constructed by using Equation (2). Four possible sources of heterogeneity are examined for the trust regression: male vs. female; education (>= vs. < high school); birth cohort (>= vs. < 1980); and whether one was working in manufacturing sector in 2016 when surveyed for the trust regression. The former three are examined for the nationalism regression. Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-5, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 6-9. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-5 and 6-9, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 10: Effects on Trust and Nationalism: Accounting for Sector Fixed Effects

	Trust in Americans			Nationalism in China	
	(1)	(2)	(3)	(4)	(5)
Export tariff	-0.3948^{***}	-0.3951^{***}	-0.4338^{**}	2.4872^{***}	2.4391^{***}
	(0.1162)	(0.1164)	(0.1705)	(0.8456)	(0.8672)
Public sector		0.0244	0.0131	0.1228^{***}	0.1205^{**}
		(0.0208)	(0.0234)	(0.0407)	(0.0612)
Other sector		0.0023	0.0009	-0.0175	-0.0288
		(0.0157)	(0.0176)	(0.0365)	(0.0544)
Export tariff X public			0.2002		0.0167
			(0.2036)		(0.4626)
Export tariff X other			0.0251		0.1620
			(0.2454)		(0.4689)
Log GDP per capita	-0.0569	-0.0587	-0.0584	-0.2248	-0.2271
	(0.0559)	(0.0557)	(0.0557)	(0.5685)	(0.5693)
Export tariff level	City	City	City	Province	Province
Num. clu.	115	115	115	53	53
Num. obs.	106667	106667	106667	4829	4829
R-sq.	0.5956	0.5955	0.5955	0.0662	0.0662
CIC 1-digit FEs	Yes				
Individual FEs	Yes	Yes	Yes		
Provincial FEs				Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-3, and a two-year repeated cross-section (2013 and 2018) for columns 4-5. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Export tariff is constructed by using Equation (2). Column 1 controls for all 20 industry dummies at the CIC 1-digit level and one additional dummy for those who are not any of the 20 industries, columns 2-5 control for dummies for sector of employment (public, private, and other (e.g., the unemployed and current students)). Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-3, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 4-5. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-3 and 4-5, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

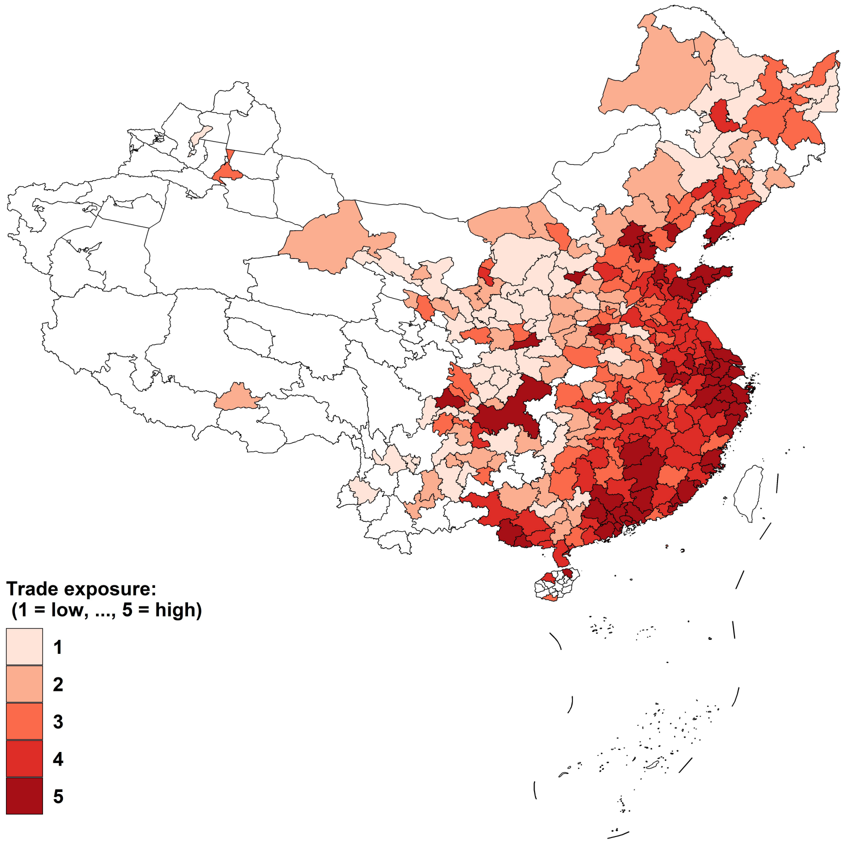
Table 11: Effects on Baidu Search Index: US Tariffs on Chinese Exports

	Baidu search per capita		
	(1)	(2)	(3)
Export tariff	0.0589^{***}	0.0589^{***}	0.0385^{***}
	(0.0081)	(0.0082)	(0.0078)
Broadband per capita		0.0014	0.0014
		(0.0016)	(0.0017)
Export tariff X broadband			0.0794^{**}
			(0.0363)
Log GDP per capita	−0.0016	−0.0016	−0.0015
	(0.0018)	(0.0018)	(0.0018)
Dep. var. mean	0.0029	0.0028	0.0028
Dep. var. SD	0.0085	0.0083	0.0083
Export tariff level	City	City	City
Num. clu.	283	283	283
Num. obs.	2283	2259	2259
R-sq.	0.9000	0.8972	0.8991
City FEs	Yes	Yes	Yes
Province-year FEs	Yes	Yes	Yes

Notes: Unit of observation is the city-year. The sample is a city-year panel spanning from 2011-2018 for 283 Chinese cities. Baidu search per capita measures the frequency of searching "US-China trade war" or "trade war" on Baidu of each city in a given year, normalized by population. Export tariff is constructed by using Equation (2). Broadband per capita is the number of broadband of each city in a given year, normalized by population. Both export tariff and broadband per capita are demeaned. Robust standard errors in parentheses, clustered at the city level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

A Additional Figures and Tables

Panel A. City-level distribution of trade exposure in 2017



Panel B. Provincial-level distribution of trade exposure in 2017

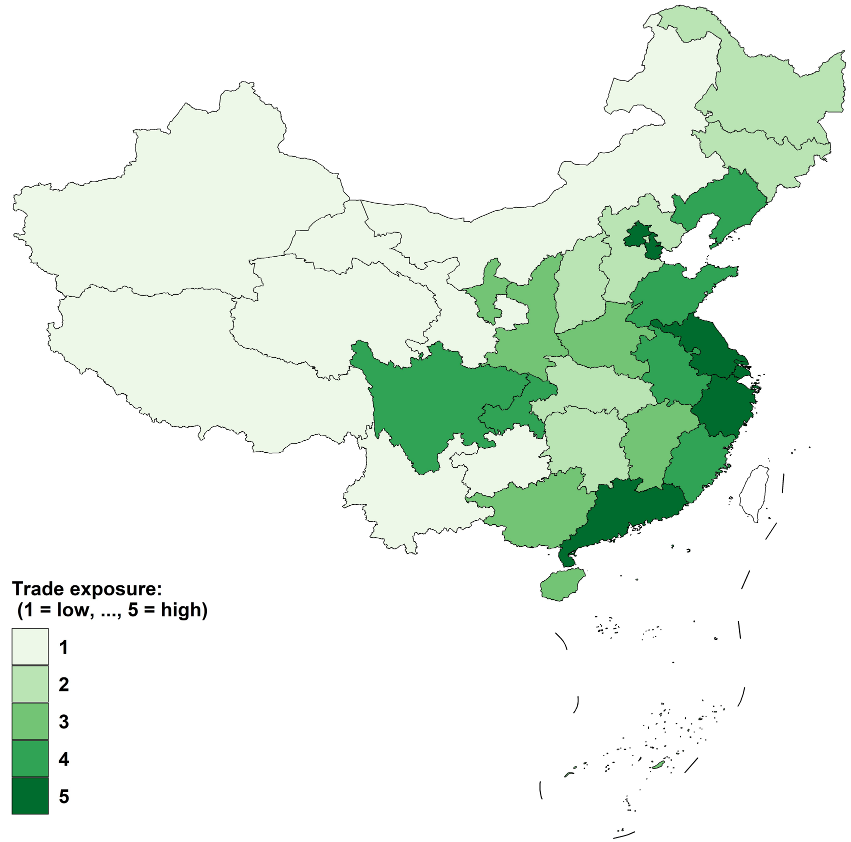
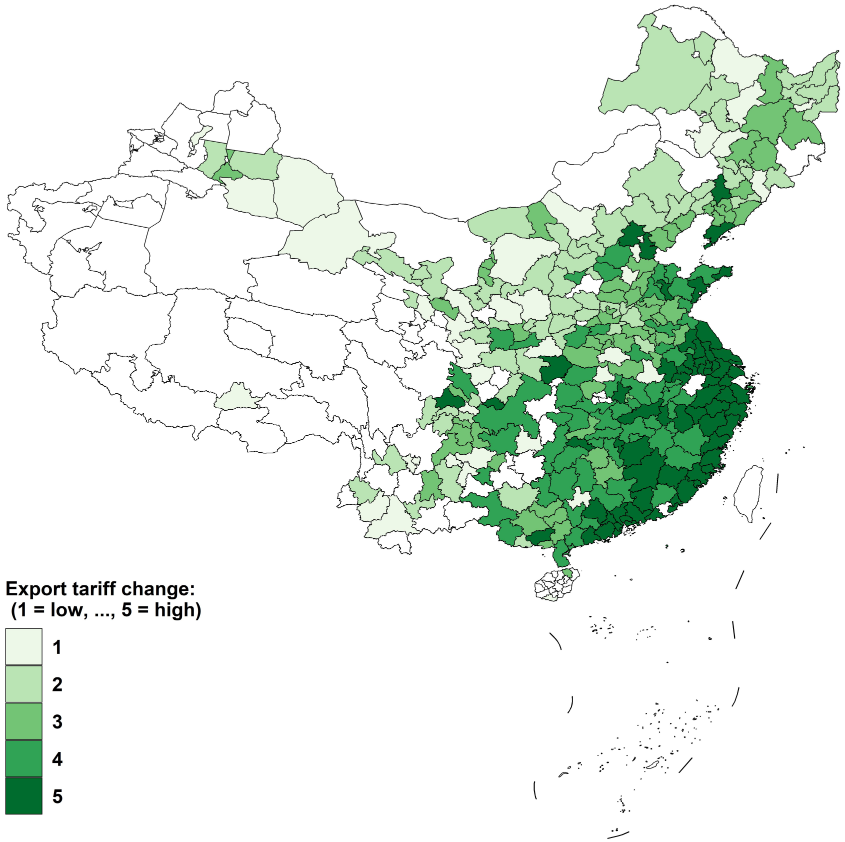


Figure A1: Spatial Distribution of US-Specific Trade Exposure in 2017

Notes: Panels A and B plot the spatial distribution of the 2017 trade exposure measure at the city- and provincial-level, respectively.

Panel A. City-level distribution of export tariff change from 2017 to 2018



Panel B. Provincial-level distribution of export tariff change from 2017 to 2018

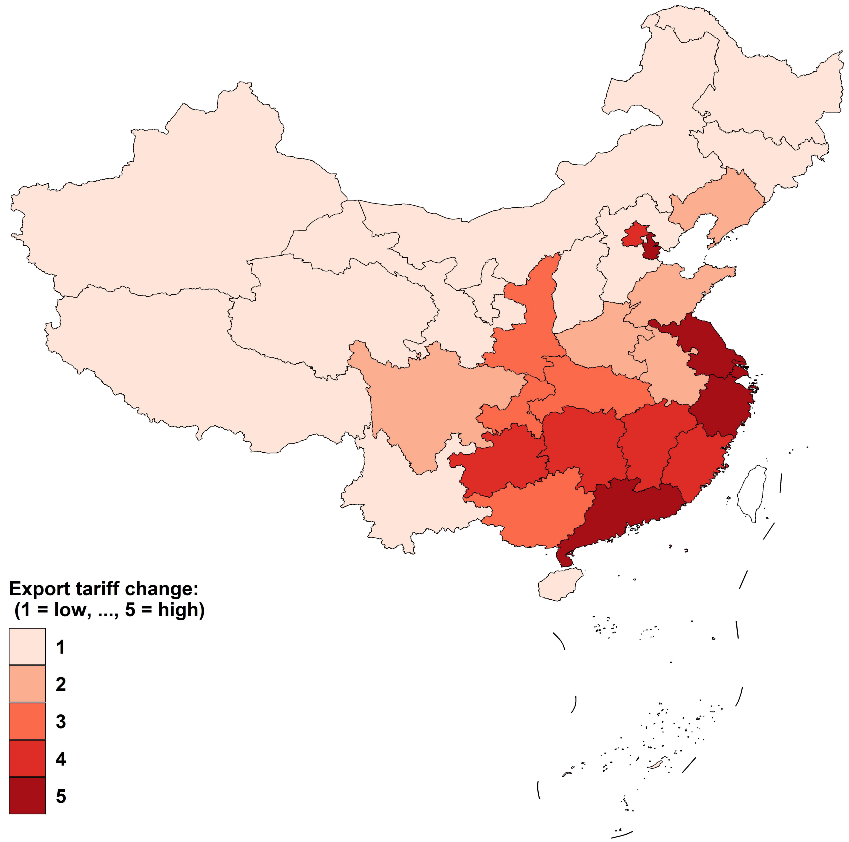


Figure A2: Spatial Distribution of Changes in US Tariffs on Chinese Exports from 2017 to 2018

Notes: Panels A and B plot the spatial distribution of changes in weighted US tariffs on Chinese exports from 2017 to 2018 at the city- and provincial-level, respectively.

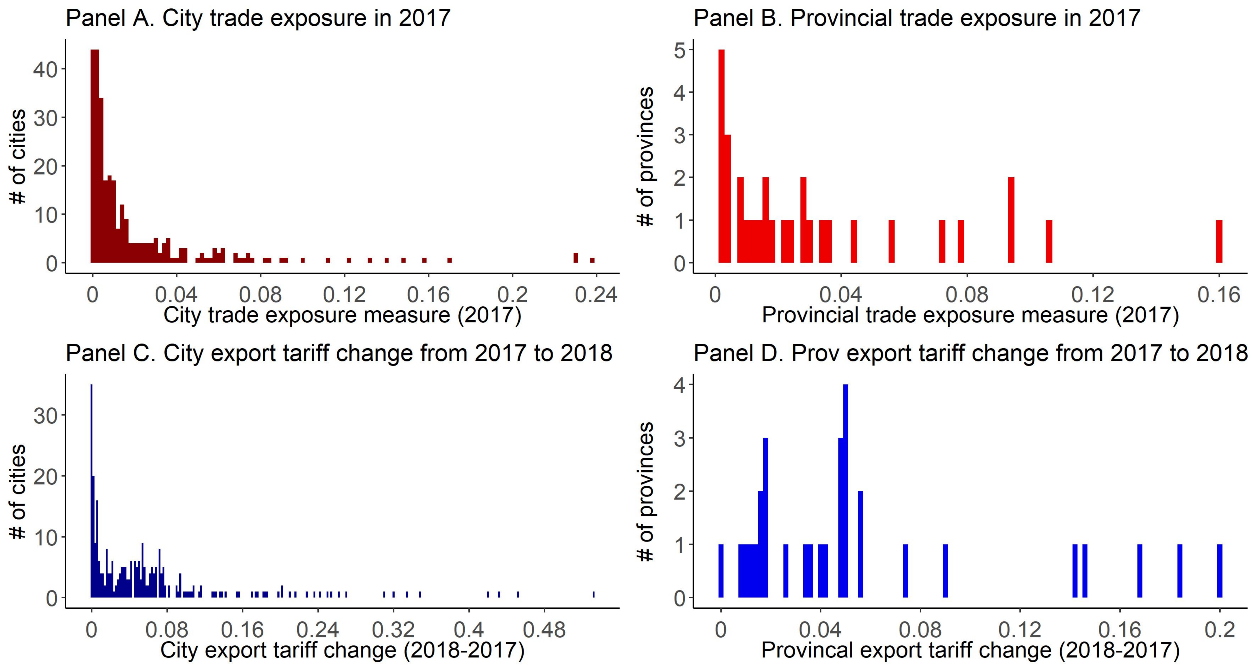


Figure A3: Distribution of Trade Exposure and Export Tariff Measures

Notes: Panels A and B (C and D) plot the distribution of the 2017 trade exposure measure (the 2018 export tariff measure) at the city and provincial level, respectively.

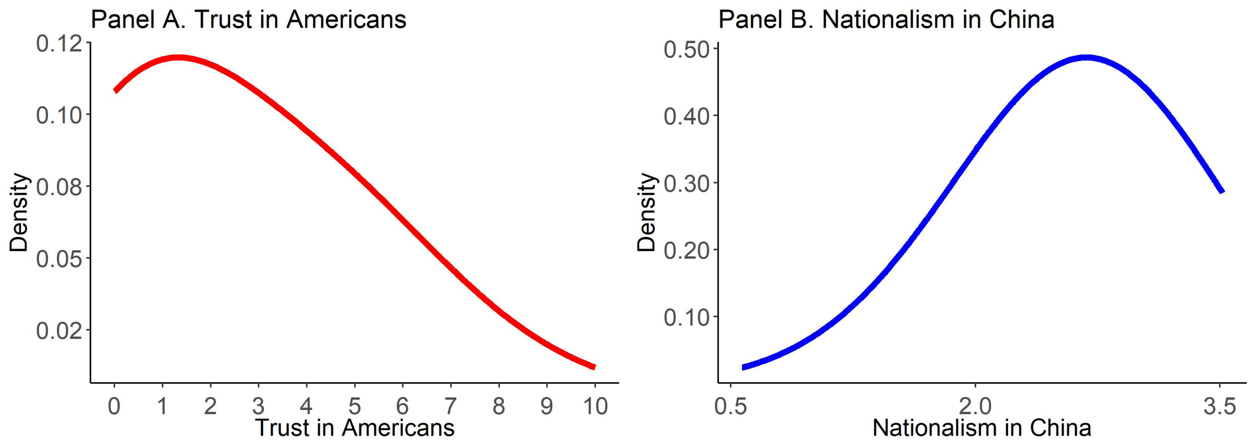


Figure A4: Density of Trust in Americans and Nationalism in China

Notes: Panels A and B plot the density of trust in Americans and nationalism in China, respectively.

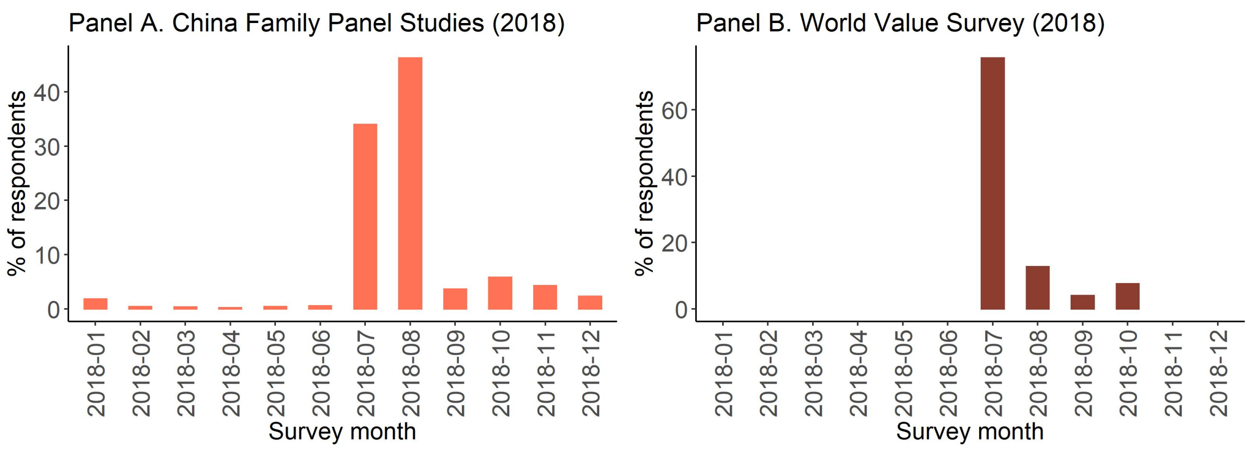


Figure A5: Percentage of Respondents by Survey Month in 2018

Notes: Panels A and B plot the monthly percentage of respondents surveyed in the 2018 wave of the CFPS and the WVS, respectively.

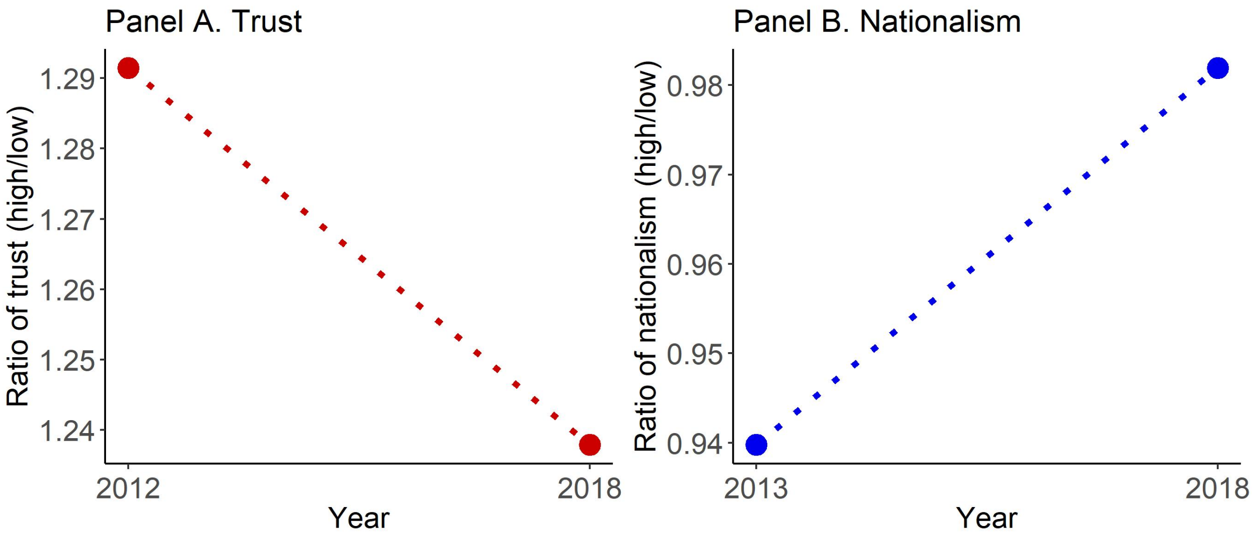


Figure A6: Convergence in Trust in Americans and Nationalism in China

Notes: Panels A and B plot the patterns of convergence in trust in Americans and nationalism in China, respectively. In 2012 (2013), I plot the ratio of the average level of trust in Americans (nationalism in China) of high-trade exposure cities (provinces) to that of low-trade regions. In 2018, I add the change in trust/nationalism induced by the trade war using the product of the export tariff change between 2012/2013 and 2018 and the estimated coefficient in column 1/5 of Table 4 to the 2012/2013 average level of trust/nationalism, then plot the ratio of the average level of newly-calculated trust/nationalism of high-trade exposure cities (provinces) to that of low-trade regions.

Table A1: Effects on Trust and Nationalism: US Tariffs on Chinese Exports (Robustness Check)

	Trust in Americans				Nationalism in China		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export tariff	-0.3794^{***}	-0.3815^{***}	-0.3338^{***}	-0.3661^{***}	1.9820^{***}	2.6462^{***}	2.5503^{***}
	(0.0938)	(0.1055)	(0.1062)	(0.1134)	(0.6176)	(0.7720)	(0.7819)
Log GDP per capita		−0.0576	−0.0655	−0.0378		−0.2693	−0.2674
		(0.0556)	(0.0554)	(0.0559)		(0.5742)	(0.5756)
Export tariff level	City	City	City	City	Province	Province	Province
Num. clu.	126	115	115	115	53	53	53
Num. obs.	115220	106667	107497	67648	4854	4854	4829
R-sq.	0.5975	0.5955	0.5962	0.5328	0.0400	0.0657	0.0641
Individual FEs	Yes	Yes	Yes	Yes			
Provincial FEs					Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables		Yes	Yes	Yes		Yes	Yes
Education FEs X year FEs			Yes				Yes
Balanced panel				Yes			

Notes: Unit of observation is the individual-year. The sample is a four-year panel (2012, 2014, 2016, and 2018) for columns 1-4, and a two-year repeated cross-section (2013 and 2018) for columns 5-7. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust); nationalism in China is an index obtained from a principal component analysis based on three variables measuring various dimensions of nationalism. Export tariff is constructed by using Equation (2) with time of per worker export measures fixed in 2010. Control variables include age dummies, education-level dummies, and city GDP per capita (logged) for columns 1-4, and gender dummy, age dummies, education-level dummies, and provincial GDP per capita (logged) for columns 5-7. Columns 3 and 7 replace educational-level dummies with education-by-year dummies. Column 4 uses a balanced panel. Robust standard errors in parentheses, clustered at the city and province-year level for columns 1-4 and 5-7, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A2: Construction of the Nationalism Index Using Principal Component Analysis

	2013		2018	
	Eigenvalue	PVE	Eigenvalue	PVE
	(1)	(2)	(3)	(4)
Factor 1	1.0671	0.3796	1.1192	0.4176
Factor 2	0.9920	0.3280	0.9558	0.3045
Factor 3	0.9366	0.2924	0.9131	0.2779

Notes: The table presents the results of using a principal component analysis method to construct the nationalism index. Columns 1 and 3 are the eigenvalues for the 2013 and 2018 data, respectively. Columns 2 and 4 are the PVEs (proportion of variance explained) for the 2013 and 2018 data, respectively. Taken together, it suggests that only one dimension of information (i.e., one index) can be singled out of the three variables, which is consistent with Lan and Li (2015) who use the 2001 and 2007 data of the WVS to construct nationalism index.

Table A3: Summary Statistics for Additional Variables

	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
Panel A. Placebo outcomes					
Trust in strangers	109571	2.0596	2.1369	0	10
Trust in foreigners	4949	1.9018	0.6738	1	4
Panel B. Control variables from the CFPS					
Age	122564	44	18	9	102
Education	121630	2.5526	1.3329	1	8
Log family income per capita	118861	8.9509	1.3904	0	14.4066
Panel C. Control variables from the WVS					
Age	4854	44	15	18	75
Education	4829	3.8242	2.4258	0	9
Income	4642	4.2385	1.8596	1	10
Gender	4854	0.4732	0.4993	0	1
Panel D. Additional regional variables					
Log provincial GDP per capita: 2010-2018	279	10.3297	0.4319	9.2522	11.5332
Log city GDP per capita: 2010-2018	2634	10.3019	0.5550	8.4502	12.0082
City broadband per capita: 2010-2018	2591	0.1899	0.1342	0.0101	2.2470

Notes: In Panel A, trust in strangers and foreigners are categorical variable ranging from 0 (1) to 10 (4), obtained from the China Family Panel Studies and the World Values Survey, respectively. Panel B reports summary statistics of controls from the CFPS, including age, education-level categories, and family income per capita. Panel C reports summary statistics of controls from the WVS, including age, education-level categories, income-level categories, and gender dummy. Panel D reports summary statistics of regional variables, including provincial or city GDP per capita and city broadband per capita, obtained from the Chinese City and Provincial Statistical Yearbooks. Refer to this table for data sources and variable definitions in this paper.

Table A4: Effects on Trust in Americans: Parallel Pre-trends Assumption Test

	Trust in Americans			
	(1)	(2)	(3)	(4)
Trade exposure (2010) X 2012	0.0153	0.0367		
	(0.1731)	(0.1862)		
Trade exposure (2010) X 2014	−0.1514	−0.1452		
	(0.2309)	(0.2097)		
Export tariff (2010) X 2012			−0.0978	−0.0879
			(0.4475)	(0.4480)
Export tariff (2010) X 2014			0.6393	0.6140
			(0.6551)	(0.6424)
Trade/tariff level	City	City	City	City
Num. clu.	114	114	125	125
Num. obs.	83894	83051	90013	89093
R-sq.	0.6475	0.6465	0.6528	0.6517
Individual FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Control variables		Yes		Yes

Notes: Unit of observation is the individual-year. The sample is a three-year panel (2012, 2014, and 2016) for columns 1-4. The omitted group in the regressions is the interaction between the trade exposure/export tariff variable and the 2016 dummy. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust). Export tariff is constructed by using Equation (2). Control variables include age dummies and education-level dummies. Robust standard errors in parentheses, clustered at the city level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A5: Long-Run Effects on Trust in Americans

	Trust in Americans	
	(1)	(2)
Trade exposure (2010) X 2012	0.0468	−0.0243
	(0.1369)	(0.1811)
Trade exposure (2010) X 2014	−0.1174	−0.1562
	(0.2185)	(0.2365)
Trade exposure (2010) X 2018	-0.3840^{***}	-0.4899^{***}
	(0.1368)	(0.1709)
Trade exposure (2010) X 2020	-1.0660^{***}	-1.1189^{***}
	(0.1553)	(0.1610)
Trade exposure level	City	City
Num. clu.	115	115
Num. obs.	126530	61066
R-sq.	0.5582	0.4941
Individual FEs	Yes	Yes
Time FEs	Yes	Yes

Notes: Unit of observation is the individual-year. The sample is a five-year panel (2012, 2014, 2016, 2018, and 2020) for columns 1-2. The omitted group in the regressions is the interaction between the trade exposure variable and the 2016 dummy for columns 1-2. The outcomes are standardized (mean=0, SD=1); trust in Americans is a categorical variable ranging from 0 (extremely low trust) to 10 (extremely high trust). Robust standard errors in parentheses, clustered at the city level for columns 1-2. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B A Model of Trade and Identity

Following the social identity literature, this section presents a simple model of bilateral trade policy and social identity, building upon the models of Shayo (2009, 2020) and Grossman and Helpman (2021). The model treats policy changes as exogenous, because the empirical focus of the paper is on how exogenous shifts in trade policy by a foreign partner shapes domestic citizens' identity choices. Specifically, I model how exogenous shifts in US trade policies toward China affect Chinese citizens' identity choices between being US-friendly reflecting a more global cosmopolitan orientation and being nationalistic, or aligning with the Chinese nation.

B.1 The Model

I consider a simple setup in which a Chinese citizen derives utility from income and from a social identification process which further consists of two components: *(i)* a perceived utility gain from identifying with a group that enjoys a high status (an affective factor, referred to as "group status"), and *(ii)* a perceived disutility when a citizen identifies with a group whose prototypical member is very different from herself (a cognitive cost, referred to as "perceived distance"). Formally, when identifying with social group J, citizen i's utility is defined as follows:

$$U_{iJ} = \pi_i + \gamma S_J - \beta d_{iJ}, \tag{B1}$$

where π_i is citizen i's income, S_J is group J's status, and d_{iJ} is citizen i's perceived distance from group J. γ and β are positive constants. The citizen i evaluates the utility from identifying with different groups J, and chooses the social identity J which maximizes her utility. I will further define S_J and d_{iJ} below.

Social Groups. Following Besley and Persson (2021), I consider two social groups in Chinese society which are mutually exclusive. One group is ideologically more open and holds favorable attitudes toward the US, while the other is less open and aligns with the Chinese nation and thus is much more nationalistic. The two social groups are referred as "the US-friendly" and "Chinese" (or "the nationalistic") groups and denoted by US and CN, respectively.[38] Thus, social group $J \in \{US, CN\}$. It is worth pointing out that group membership resides in one's mind. It cannot be coerced, nor does it need to be accepted by other members in the group with which one identifies.

Group Status. I now turn to the two components of utility from social identification. First, if one identifies herself with a particular group J, then she will enjoy utility derived from J's group status S_J:

$$S_J(t) = \Pi_J(t), \text{for } J \in \{US, CN\}, \tag{B2}$$

where $\Pi_J(t)$ is group J's material payoffs, which I assume is a function of trade openness t and the average member's individual income $\pi_J(t)$ (e.g., Shayo, 2009; Grossman and Helpman, 2021).[39]

[38] More broadly, "the US-friendly" can be viewed as "the cosmopolitan" as defined in Besley and Persson (2021).

[39] Like Abramson and Shayo (2022) and Grossman and Helpman (2021), I do not consider the status of the reference group of group J directly, since it does not affect the qualitative analysis but is analytically cumbersome. That is, I do not consider social comparison at the group level. This is a reasonable simplifying way in many cases, for example, see Balliet, Wu and De Dreu (2014). Moreover, nor I consider exogenous determinants of group status since they can be modeled in a very flexible way and thus will not affect the analysis.

Consider a policy bundle that enhances China's trade liberalization with the US. The policy bundle can be thought of as a combination of various trade-enhancing policies, with tariffs imposed by both countries on each other's exports being the most prominent negative policy. Both the Chinese government and the US government can make decisions which affect this policy bundle. In China, the policy bundle affects people in different regions differently since some regions have advantages in exporting goods to the US but the others do not. Denote region by R; a region can be a city or a province in the empirical analysis, depending on the available data.

Let t be the degree of trade liberalization between China and the US, and e_R be the extent of US-specific trade exposure of citizens living in region R. As noted earlier, a relevant comparison group for people to evaluate group status is a city or province where they reside. Without loss of generosity, I assume $t \in [0,1]$ and $e_R \in [0,1]$. A Chinese citizen i's income π_i is given by:

$$\pi_i(t) = (1 + e_R t) y_i, \tag{B3}$$

where y_i is citizen i's income absent bilateral trade. It is easy to see that $\frac{\partial \pi}{\partial t} > 0$, $\frac{\partial \pi}{\partial e_R} > 0$, and $\frac{\partial \pi}{\partial (e_R t)} > 0$.

To fix the ideas, I only consider two types of regions: $R \in \{H, L\}$, where H denotes a high-trade region and L a low-trade region, defined with respect to trade with the US. A Chinese citizen i belongs to either H or L. Denote an average citizen in region H (L) by h (l), then $i \in \{h, l\}$. In this regard, types of citizens are defined by the type of region in which they live.

By defining trade regions and social groups as above, this study considers a 2×2 setting, under which this study is particularly interested in how a representative citizen from a trade region (h or l) chooses her social identity (between US and CN) in response to trade policy changes.[40]

The economic status of the US-friendly group is higher when the trade liberalization degree is sufficiently high (say, as it was during the pre-trade war period). To capture this fact, I model group material payoffs in the following way for the two groups. First, I use a representative citizen in a high-trade region h to proxy for a prototypical member of the US-friendly group. Thus, for group US, we have $\Pi_{US}(t) = \pi_{US}(t) = \pi_h(t) = (1 + e_H t) y_h$. An average citizen in high-trade region may have a limited region-based information set and economically care much more about her own region. Moreover, people regard residential place as one of the most important determinants of their social identity, as noted by Shayo (2009, p. 151).

Second, I assume that members in group CN care about all Chinese citizens' economic payoffs. For example, doing trade with the US contributes to overall economic growth in China, so a citizen who is from low-trade region l but considers China as a whole also may take pride in overall growth, even though she benefits less from it. Hence, I define the material payoffs of a prototypical member of group CN as a weighted average of material payoffs of h and l, representative agents of high- and low-trade regions, respectively. Thus, for group CN, we have $\Pi_{CN}(t) = \pi_{CN}(t) = \alpha \pi_h(t) + (1-\alpha)\pi_l(t) = \alpha(1 + e_H t) y_h + (1-\alpha)(1 + e_L t) y_l$, where $\alpha \in [0,1]$.[41]

[40] I do not consider the following two situations: *(i)* one can identify with both groups and *(ii)* some people are always US-friendly or nationalistic, which are not restrictive simplifications since I focus on representative citizens in different regions who are likely to fit in none of the two cases. In other words, representative citizens' identities are fungible and they identify with only one group at a time.

[41] There are two noteworthy points. First, $\Pi_{CN}(t) = \pi_h(t) = \Pi_{US}(t)$ when $\alpha = 1$, that is, $\Pi_{US}(t)$ can be modeled as a special case of the weighted average of material payoffs of h and l. Second, an average citizen from low-trade regions l

Perceived Distance. A Chinese citizen i's disutility from perceived distance is determined by the sociopolitical environment. One will bear a cognitive cost if she identifies with a group whose attributes are not very similar to her, or if she does not conform to the prescribed behaviors (or actions) of her group peers, especially those with whom she has daily social interactions. Before the trade war, I define perceived distance as a function of whether one lives in a high- or low-trade region, represented as follows:

$$d_{iJ} = (T_i - T_J)^2, \text{ for } i \in \{h, l\} \text{ and } J \in \{US, CN\}, \tag{B4}$$

where T indicates whether citizen i (or group J) has the attribute of doing more trade with the US. The simple intuition is that one will incur a disutility if she identifies with a group not similar to herself. If a person lives in an area of low trade, she will feel different from the expected profile of US-friendly people, which is that they live in a high trade region (with more FDI, trade, and foreigners, etc). Similarly, if one lives in a high-trade area, she will perceive a greater distance with the expected profile of the group identifying with the Chinese nation, which are those who live in a less globalized environment. Here $T_{US} = 1$ and $T_{CN} = 0$ for social groups, and $T_h = 1$ and $T_l = 0$ for citizens in different trade regions.

Using this logic, for a representative high-trade citizen h, we have $d_{hUS} = 0$ and $d_{hCN} = 1$, which reinforces the decision to identify with the US-friendly group. This captures the idea that living in an international environment (e.g., more foreign trade and investment as well as cultural exchange such as watching more Hollywood movies) makes one more similar to an average US-friendly citizen and thus feel distant from the nationalistic group. Similarly, for a representative low-trade citizen l, we have $d_{lUS} = 1$ and $d_{lCN} = 0$, reflecting the fact that a citizen with little exposure to an international environment perceives herself being not similar to, and thus more distant from, those globalists or cosmopolitans (the US-friendly group). In summary, before the trade war, the distance reinforced high-trade (low-trade) citizens to identify with the US-friendly group (the Chinese nation).

After the trade war, I add a second term to the perceived distance function to reflect the widespread feeling of injustice felt by all Chinese. The function now is represented as follows:

$$d_{iJ} = (1 - w_N)(T_i - T_J)^2 + w_N(N_i - N_J)^2, \text{ for } i \in \{h, l\} \text{ and } J \in \{US, CN\}, \tag{B5}$$

where N indicates whether citizen i (or an average member of group J) behaves in a nationalistic way. $w_N \in [0, 1]$ captures the relative salience attached to N among citizens or more generally the salience of group membership. Given w_N, citizens' attention paid to T is $1 - w_N$. An intuitive way of interpreting the new distance term is that behaving in a patriotic manner is a salient action but living in a certain trade region is a silent attribute. The relative salience of w_N (or, the importance of T versus N) depends on the sociopolitical environment. Relatedly, Bonomi et al. (2021) show that an increase in salience of cultural values would lead to a rise in cultural conflict (socially progressive versus conservative) but a fall in redistributive conflict (high versus low tax).

Nationalistic and anti-Americans sentiment and behaviors have increased among Chinese citizens since the trade war was launched. Chinese citizens called the CEO of ByteDance a traitor

may put more weights on $\pi_l(t)$, that is, it is likely the case that $\alpha \in [0, 0.5)$. The representation of $\Pi_{CN}(t)$ in this paper is consistent with Shayo (2009) and Grossman and Helpman (2021).

but regarded Meng Wanzhou of Huawei as a national hero (Xin and Xue, 2021). Chinese patriotic films became very popular (Shepherd, 2021). Many Chinese boycotted western brands that stooped sourcing Xinjiang cotton due to human rights concerns, and Chinese celebrities cut ties with such brands, including Nike (Hong, 2021).

In this sociopolitical environment, all pro-US behaviors are viewed as disloyal to China, regardless of where one resides. Thus, everyone is expected to behave in a nationalistic way, for example, by boycotting US goods (e.g., not buying Nike shoes or not watching Hollywood movies). That is, $N_h = N_l = 1$ for all citizens after being exposed to the exogenous shock of the trade war. However, the expected behavior of a person identifying as US-friendly is to not boycott US goods or have positive feelings favoring the US, that is, $N_{US} = 0$. Acting nationalistically creates no distance with the Chinese nation, and the expected behavior of those aligning with the Chinese nation is to act in a nationalistic way, we thus have $N_{CN} = 1$.

Consequently, after the trade war, for a representative high-trade citizen h, we have $d_{hUS} = w_N$ and $d_{hCN} = 1 - w_N$.[42] Compared to before, she will perceive a relatively shorter distance to the Chinese nation as long as w_N is sufficiently large. That is, behaving nationalistically but choosing a US-friendly identity creates an internal conflict. This conflict between the expected and actual feelings and behaviors creates a new perceived distance with the US-friendly group. Meanwhile, for a representative low-trade citizen l, we have $d_{lUS} = 1$ but $d_{lCN} = 0$, the perceived distance with the US-friendly group remains significant. Overall, after the trade war, citizens in high–trade regions are more likely to align with the Chinese nation, while those in low-trade regions remain close to the Chinese nation.

Decision Rule. We say citizen i is more likely to identify with social group J if S_J and d_{iJ} are increasing and decreasing with the degree of trade liberalization t. We write the utility maximization problem of citizen i that identifies with group J as follows:

$$\text{Max}_J \; U_{iJ}(t) = \pi_i(t) + \gamma S_J(t) - \beta d_{iJ}$$
$$\text{s.t. } i \in \{h, l\},\; J \in \{US, CN\},\; t \in [0, 1],$$

where γ and β are positive utility parameters assumed to be constant.[43] As proposed by Shayo (2020), a decision rule can be defined: *for a given t, J_o is a chosen profile of social identities such that for $i \in \{h, l\}$, we have $U_{iJ_o}(t) > U_{iJ'_o}(t), \forall J'_o \in \{US, CN\}$.* Two implications follow: citizens are more likely to identify with social groups *(i)* that enjoy a higher status (higher S_J), and *(ii)* that they perceive as more similar to themselves (lower d_{iJ}). In our context, citizens reside in either high-trade or low-trade regions and then choose to whether identify with the US-friendly group or the Chinese nation after having experienced an exogenous shift in trade liberalization degree. The overall chosen profile of the model consists of two sub-profiles for representative agents h and l, respectively. Above, we have shown that the US-China trade war is expected to reduce identification

[42] It is possible that $d_{hCN} = 0$ after the trade war if high-trade regions' trade with the US drops sufficiently (i.e., all high-trade regions become low-trade regions due to the trade war). I do not consider this case because I focus empirically on a short time period that did not witness a drop in trade between China and the US (see Panel B of Figure 2). Another possibility for citizen i to change T is to migrate to another region. However, this might be economically costly in reality as well as politically unnecessary since because no one cares about where one resides after the trade war. In both cases, the theoretical results will be reinforced.

[43] The former (γ) allows individuals to take pride in group status, while the latter (β) "punishes" individuals if they identify with a group not similar to them or deviate from the group behaviors or norms.

as US-friendly and increase identification with the Chinese nation, especially in regions with more ex ante trade with the US.

B.2 Empirical Predictions

I now derive and discuss the empirical hypotheses produced by the model that will be taken to the data. I begin with the social identification pattern during the pre-trade war period. In this case, citizens identify with social groups based only on the most distinguishable attribute (i.e., the trade with the US). Deviating from this would incur a sufficiently large disutility. We thus have the following prediction.

Prediction 1. *When China's trade liberalization degree with respect to the US is sufficiently high, citizens in regions doing more (less) trade with the US are more likely to identify with the US-friendly group (the Chinese nation).*
Proof. See Appendix B.3.

Next consider how the US-China trade war affects social identification of citizens in high-trade regions. First, given that the trade war occurred mostly through increased tariffs that may have a negative impact on the labor market, a region exposed more to the trade with the US would be economically hit harder by the trade disruptions. This results in the economic payoffs of a representative high-trade citizen (π_h) to decrease by a larger amount, which reduces the social status of the US-friendly group (S_{US}) because (π_{US}) falls. Second, the trade war awakens the salience of national identity in the sociopolitical environment, so that all pro-US behaviors are viewed as disloyal to China, increasing the perceived distance of those in high-trade areas with the US-friendly group because $N_h = 1$ but $N_{US} = 0$. Furthermore, citizens focus their attention mostly on whether peers behave nationalistically or not. That is, w_N increases dramatically, approaching to one. Thus, for an average high-trade citizen, being similar to a prototypical US-friendly citizen does not matter since this attribute is made silent; however, behaving nationalistically but choosing a US-friendly identity would be very costly for her. Taken together, we have an informative prediction as follows.

Prediction 2. *A representative citizen in regions doing more trade with the US is more likely to identify with the Chinese nation than with the US-friendly group if China's trade liberalization degree with respect to the US exogenously shifts from a high to low level. There exist two main channels: (i) the trade war reduces the economic status of the US-friendly group more than it reduces the economic status of the nationalistic group; and (ii) her perceived distance with the US-friendly group becomes larger because of a new widespread view that US-friendly behavior is unpatriotic.*
Proof. See Appendix B.3.

This is the main empirical prediction of this paper. Here I provide a brief description of the proof. For the first half, consider a representative citizen in high-trade region h. Her utility from identifying with CN and US are given by $U_{hCN}(t)$ and $U_{hUS}(t)$, respectively. Let $\Delta U = U_{hCN}(t) - U_{hUS}(t)$, it is easy to show $\frac{\partial \Delta U}{\partial t} < 0$. Thus, a region that experiences a larger reduction in t will see a greater decline in identification with the US-friendly group. To see this more clearly, consider the two channels. Since $J_o \in \{CN\}$ for $i = h$, the equilibrium condition implies that: $U_{hCN}(t) > U_{hUS}(t)$, that is, $\gamma[S_{CN}(t)-S_{US}(t)] > \beta[d_{hCN}-d_{hUS}]$. Therefore, we need to show that $\Delta S = S_{CN}(t)-S_{US}(t)$ will increase and $\Delta d = d_{hCN}-d_{hUS}$ will decrease. Intuitively, for a high-trade Chinese citizen to identify with the Chinese nation but not with the US-friendly group, the group status of CN needs to be sufficiently greater than that of US, and her perceived distance from CN needs to be sufficiently smaller than from US. First, it is easy to show that $\frac{\partial \Delta S}{\partial \pi_{US}} < 0$. Since $\frac{\partial \pi}{\partial t} > 0$, it follows that $\frac{\partial \Delta S}{\partial t} = \frac{\partial \Delta S}{\partial \pi_{US}} \frac{\partial \pi_{US}}{\partial t} < 0$. Second, we can show that $\frac{\partial \Delta d}{\partial w_N} < 0$. By the logic explained earlier, this is due to the fact that w_N exogenously appears after the trade war as the the US-friendly behavior is viewed as unpatriotic.

Related to this prediction, it is straightforward to show that a representative citizen in a low-trade region always identifies with the Chinese nation with or without the trade war, that is, her social identification pattern is stable, which theoretically justifies treating low-trade regions as a control group in the empirical analysis.

B.3 Proofs

Prediction 1.

Proof. Note that in absence of the trade war (i.e., when t is sufficiently high), we have $T_h = 1$ and $T_l = 0$, $T_{US} = 1$ and $T_{CN} = 0$. First, consider a representative citizen in high-trade regions h. Her utility of identifying with the US-friendly group is given by: $U_{hUS}(t) = \pi_h(t)+\gamma S_{US}(t)-\beta d_{hUS}(t) = \pi_h(t)+\gamma\pi_h(t)$; and her utility of identifying with the Chinese nation is given by: $U_{hCN}(t) = \pi_h(t)+\gamma S_{CN}(t)-\beta d_{hCN}(t) = \pi_h(t)+\gamma[\alpha\pi_h(t)+(1-\alpha)\pi_l(t)]-\beta$. Therefore, $U_{hUS}(t)-U_{hCN}(t) > 0$, that is, $U_{hUS}(t) > U_{hCN}(t)$.

Second, consider a representative citizen in low-trade regions l. Her utility of identifying with the US-friendly group is given by: $U_{lUS}(t) = \pi_l(t)+\gamma S_{US}(t)-\beta d_{lUS}(t) = \pi_l(t)+\gamma\pi_h(t)-\beta$; and her utility of identifying with the Chinese nation is given by: $U_{lCN}(t) = \pi_l(t)+\gamma S_{CN}(t)-\beta d_{lCN}(t) = \pi_l(t)+\gamma[\alpha\pi_h(t)+(1-\alpha)\pi_l(t)]$. Therefore, we have $U_{lUS}(t)-U_{lCN}(t) < 0$, that is, $U_{lUS}(t) < U_{lCN}(t)$, as long as the following assumption holds: $\beta > \gamma[(1-\alpha)(\pi_h(t)-\pi_l(t))]$, which says that the utility parameter attached to the cognitive cost needs to be large enough so that one will not identify with a social group that is not similar to herself.

Prediction 2.

Proof. Note that $N_h = 1$ since now the trade war has occurred (i.e., t experienced a sufficiently large reduction). For the first half, consider a representative citizen in high-trade regions h. When she identifies with the US-friendly group, her utility is given by: $U_{hUS}(t) = \pi_h(t)+\gamma S_{US}(t)-\beta d_{hUS}(t) = (1+e_h t)y_h+\gamma[(1+e_h t)y_h]-\beta w_N$. If she identifies with the Chinese nation, her utility is given by: $U_{hCN}(t) = \pi_h(t)+\gamma S_{CN}(t)-\beta d_{hCN}(t) = (1+e_h t)y_h+\gamma\{\alpha[(1+e_h t)y_h]+(1-\alpha)[(1+e_l t)y_l]\}-\beta w_T$. Now let $\Delta U = U_{hCN}(t)-U_{hUS}(t)$, then we have:

$$\frac{\partial \Delta U}{\partial t} = \gamma(\alpha-1)(y_h e_h - y_l e_l) < 0. \quad \text{(B6)}$$

Since $\gamma > 0$, and $\alpha \in [0,1]$, we will have $\frac{\partial \Delta U}{\partial t} < 0$ as long as $y_h e_h - y_l e_l > 0$, that is, $\frac{y_h}{y_l} > \frac{e_h}{e_l}$, which says that in absence of trade individual income in high-trade regions (or more generally, initial endowment of these regions) should be high enough. Taken together, an exogenous decrease in China's trade liberalization degree with respect to the US will increase the likelihood of a citizen in regions doing more trade with the US identifying with the Chinese nation but decrease her probability of identifying with the US-friendly group.

For the second half pertaining to the two channels, consider again a representative high-trade citizen h, who identifies with the Chinese nation: $J_o \in \{CN\}$. The equilibrium condition, $U_{hCN}(t) > U_{hUS}(t)$, implies that: $\gamma[S_{CN}(t) - S_{US}(t)] > \beta[d_{hCN}(t) - d_{hUS}(t)]$, which further require $\Delta S = S_{CN}(t) - S_{US}(t)$ to increase and $\Delta d = d_{hCN}(t) - d_{hUS}(t)$ to decrease.

The ΔS ***(group status) Channel.*** Given that $S_{CN}(t) = \alpha\pi_h(t) + (1-\alpha)\pi_l(t)$ and $S_{US}(t) = \pi_h(t)$, we have $\Delta S = S_{CN}(t) - S_{US}(t) = (\alpha - 1)\pi_h(t) + (1-\alpha)\pi_l(t)$, which yields:

$$\frac{\partial \Delta S}{\partial \pi_h(t)} = \alpha - 1 < 0. \tag{B7}$$

From $\pi_h(t) = (1 + e_h t)y_h + g$, we have $\frac{\partial \pi_h(t)}{\partial t} = e_h y_h > 0$. Thus, we have $\frac{\partial \Delta S}{\partial t} = \frac{\partial \Delta S}{\partial \pi_h(t)} \frac{\partial \pi_h(t)}{\partial t} < 0$. Since $\pi_h(t) = \pi_{US}(t)$, we finally have $\frac{\partial \Delta S}{\partial t} = \frac{\partial \Delta S}{\partial \pi_{US}(t)} \frac{\partial \pi_{US}(t)}{\partial t} < 0$. That is, an exogenous shift in China's trade liberalization degree with respect to the US from a high to low level could force high-trade citizens to identify with the Chinese nation through lowering status (i.e., material payoffs) of the US-friendly social group (i.e., $\pi_{US} \downarrow$).

The Δd ***(perceived distance/membership salience) Channel.*** When citizen h identifies with the Chinese nation CN, it is clear that $d_{hCN}(t) = 1 - w_N$. When citizen h identifies with the US-friendly group US, it also is clear that $d_{hUS}(t) = w_N$. We thus have $\Delta d = d_{hCN}(t) - d_{hUS}(t) = 1 - 2w_N$, which yields:

$$\frac{\partial \Delta d}{\partial w_N} = -2 < 0. \tag{B8}$$

That is, an increase in salience of the Chinese national identity (i.e., $w_N \uparrow$) triggered by the US-China trade conflicts could make high-trade citizens perceive a longer distance from the US-friendly group but a shorter distance from the Chinese nation, and thus identify with the Chinese nation.