

NBER WORKING PAPER SERIES

CAN EVIDENCE-BASED INFORMATION SHIFT PREFERENCES TOWARDS
TRADE POLICY?

Laura Alfaro
Maggie Chen
Davin Chor

Working Paper 31240
<http://www.nber.org/papers/w31240>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2023, Revised October 2024

We thank Pol Antràs, Dany Bahar, Andy Bernard, Filipe Campante, Paola Conconi, Jeffrey Frankel, Jeffrey Frieden, Douglas Gollin, Gordon Hanson, Beata Javorcik, Jennifer Jerit, Joseph Kaboski, Ellie Kyung, Nuno Limão, Erzo Luttmer, Giovanni Maggi, Brendan Nyhan, Vincent Pons, Carmen Reinhart, Steve Redding, John Romalis, Peter Schott, Robert Staiger, Catherine Thomas, Jonathan Vogel, and Adrian Wood for their insightful and constructive comments, and Mike Norton for generous advice on survey methods. We also thank audiences at the Yale-Cowles, NBER-ITI, North American meeting of the Econometric Society, Barcelona GSE Forum, CEPR Policy Implications of Recent Globalization Research, CEPR-STEG, CEPR-Banque de France, IMF, LIEP Kennedy School, CEPR-End of Globalization Conference, CEPR-ERWIT, Bank of Italy-ECB-World Bank Conference, ECB, IATRC Annual Meeting, Tennessee, NUS, Compnet Conference, US International Trade Commission, CR Economist Conference, PEIF Conference, for their comments and suggestions. Bashudha Dhamala, Louisa Gao, Sirig Gurung, Kelley Jiang, Sarah Jeong, Han Loong Ng, Sofia Przybylek, and Sophia Zupanc provided excellent research support. All errors are on our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2023 by Laura Alfaro, Maggie Chen, and Davin Chor. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Can Evidence-Based Information Shift Preferences Towards Trade Policy?

Laura Alfaro, Maggie Chen, and Davin Chor

NBER Working Paper No. 31240

May 2023, Revised October 2024

JEL No. D8, F1, F6

ABSTRACT

Amid public skepticism about trade, we investigate whether evidence-based information—a concise statement of a research finding—can shape preferences towards trade policy. Across survey experiments conducted over 2018-2022 on U.S. general population samples, we consistently uncover a “backfire effect”: Information that highlights benefits from trade (job gains in productive sectors or lower consumer prices) induces protectionist policy choices, particularly among Republicans. We interpret this finding through the lens of a model of prior-biased belief updating. Averting this backfire effect will require addressing the prior beliefs—specifically, over the impact of trade on jobs and trade relations with China—that we find prevalent among respondents inclined toward protectionism.

Laura Alfaro
Harvard Business School
Morgan Hall 263
Soldiers Field
Boston, MA 02163
and NBER
lalfaro@hbs.edu

Davin Chor
Tuck School of Business
Dartmouth College
100 Tuck Mall
Hanover, NH 03755
and NBER
davin.chor@dartmouth.edu

Maggie Chen
Dept. of Economics
George Washington University
2115 G ST, NW, #367
Washington, DC 20052
xchen@gwu.edu

1 Introduction

Public skepticism of free trade has been on the rise across countries, amid a growing backlash against globalization (Colantone et al. 2022). These sentiments stem in part from longstanding concerns over how openness to trade affects jobs and wages, particularly in the manufacturing sector.¹ But the recent surge in protectionism has notably also been driven “top-down” by political leaders (Goldberg and Reed 2023), who have tapped into and amplified the public’s grievances during such episodes as Brexit in the U.K., the U.S.-China trade war, and the Covid-19 supply chain disruptions.² The rise of mobile devices and social media has moreover provided political actors with platforms on which to project their messaging regularly to a broad audience. Often, the rhetoric has been skeptical (or even hostile) toward globalization, without necessarily providing objective information on the benefits and costs of openness to trade.

In this paper, we investigate whether and how *evidence-based* information on the gains and losses from trade can shape preferences towards trade policy. This research question is all the more pressing in the current political and media environment, as it gets to the issue of whether objective narratives can facilitate more informed and considered choices over trade policy from the general public. Specifically, we set out to understand whether information drawn from research, conveyed in a concise and accessible manner, can shape perceptions toward trade. Are people receptive to and willing to update their trade policy preferences in accord with such information? Or might this instead trigger unintended reactions and consequences?

To date, studies on what shapes individuals’ trade policy preferences have (barring a few exceptions) been largely silent on the role of information. Economists have conventionally viewed these preferences as mainly driven by whether openness to trade aligns with one’s economic self-interest (Baldwin 1989, Rodrik 1995), by one’s concerns about how trade will impact broader society (Mansfield and Mutz 2009), or by one’s socio-political identity (Grossman and Helpman 2021). Less is known about how the information one is exposed to can affect views toward trade. From an empirical standpoint, a key challenge lies in distinguishing the effect of information from alternative forces, including the possibility that individuals might select their information sources based on their pre-existing beliefs (Gentzkow and Shapiro 2010, 2011).

We tackle this challenge by developing a series of survey-based experiments – run annually between 2018-2022 on representative samples from the U.S. general population – that contain information treatments. The randomized assignment of participants to treatments enables us to identify the causal impact of the received information on expressed preferences over policies. This draws on the influential methodological approach, described in Haaland et al. (2023) and Stantcheva (2023), that has been pioneered in recent years to study how information shapes the public’s views in various policy domains (see Section 2 for an overview). We focus on treatments

1. Such concerns have been present since at least the mid-1990s, with some economists arguing that trade with low-income countries was responsible for low unskilled wages and rising inequality in developed countries (e.g., Wood 1995). Others however pointed to the role of within-industry specialization and evidence from the factor content of trade to argue that the effect of trade on wage inequality was small relative to other forces (see Krugman 1995, 2000). For follow-up on this debate, see Lawrence (2008), Krugman (2008), among others.

2. The Global Trade Alert has documented the recent rise in government measures that restrict international trade; see <https://www.globaltradealert.org>.

that convey evidence-based information from economics research and data related to the “China trade shock” (Autor et al. 2013, 2016, Pierce and Schott 2016), on how this affected U.S. labor markets and goods prices; in this regard, we differ from other survey-based studies (discussed in Section 2) which have explored frames or hypothetical scenarios about the effects of trade. In all, we have gathered responses from about 18,000 participants spanning five years; the consistent question format across years allows us to compare our findings over this period of rapid political developments and unprecedented disruptions in the global economy.

We designed four baseline information treatments, each on a specific employment or price effect of trade that has been highlighted in conventional trade theories (e.g., the Heckscher-Ohlin model) and documented in empirical evidence. The first two treatments focus on the relationship between trade and jobs in different sectors. In the “Trade Hurts Jobs” treatment, we provide a statement of the main finding from Autor et al. (2013), that the rise in imports from China hurt the labor market outcomes of U.S. manufacturing workers. On the other hand, the “Trade Helps Jobs” treatment describes how the growth in imports of goods from China led the U.S. to specialize more in its service sectors, as studied by Caliendo et al. (2019), with the expansion in service-sector jobs in turn driving an increase in total jobs in the U.S. Our remaining two treatments are on the effect of trade on goods prices. In “Trade Helps Prices”, we draw on Bureau of Labor Statistics data to highlight how the rise in imports from China was associated with lower prices, both for durables (such as computers) and non-durables (such as apparel). Conversely, the “Tariff Hurts Prices” treatment describes how recent U.S. tariff actions to slow down the flow of imports from China have raised the U.S. prices of tariff-affected goods and reduced U.S. real income, as analyzed in Amiti et al. (2019). Each narrative is written in simple, comparable text without technical jargon – akin to how a researcher might try to convey their findings to a general audience – and is accompanied by a figure illustrating the respective trend in jobs or prices (see Appendix A). Following the treatments, we then solicited participants’ preferences over a range of policy instruments, such as tariffs on imports, improving education and worker training, and progressive taxes.

We find that the evidence-based information we provided shifts preferences for trade policy, but in complex and unanticipated ways. On the less surprising side, participants who received the “Trade Hurts Jobs” treatment on manufacturing job losses were significantly more likely to favor protectionist measures than the no-information control group. Strikingly though, we document a “*backfire effect*” to the narratives that convey the service job gains or the consumer price benefits of openness to trade: The “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments induce a more negative view of the impact that trade has had on most Americans, as well as a stronger preference for more limits on imports. This backfire effect is quantitatively meaningful, equal to between one-sixth to one-third of the gap between Republican supporters and independents in the intensity of their protectionist preferences.

These patterns, though puzzling at first glance, are robust: They hold consistently across all five survey years. They hold when we remove the adjective “cheaper” (which may connote lower quality), or even when we take out any explicit mention of “China” from the treatment wording. They are unlikely to stem from a basic miscomprehension of the narrative, as we show that participants could, on average, correctly recall whether the received information was on the

effect of trade on jobs or on prices. We do find this protectionist response to be dampened among those who spent a longer duration on (and presumably paid more attention to) the information presented on the benefits of trade, but the effect is not reversed (i.e., the treatment coefficient does not flip signs).

This finding of a backfire effect is, to the best of our knowledge, new to the literature on public attitudes toward trade. In the related body of survey-based studies on this topic conducted by economists and political scientists, respondents have been moved to favor more protectionism when trade is framed in a negative light, but the effects of positive frames have typically been statistically indistinguishable from zero (see Hiscox 2006, Rodriguez et al. 2021, Stantcheva 2022, Coppock 2023, as further discussed in Section 2). Our results are even more sharply asymmetric, as information on the gains from trade provided in this evidence-based format actually provokes a significant protectionist response.

In the remainder of the paper, we seek to understand the mechanisms behind this backfire effect. Specifically, we examine whether one’s prior disposition toward free trade might interact in meaningful ways with the treatments, in shaping how the received information affects one’s trade policy views. Toward this end, we explore a broad set of variables identified by the trade policy literature as potential markers of an individual’s prior trade beliefs, including: proxies of personal economic exposure (e.g., sector of employment); measures of concern about the societal impact of trade (e.g., over income inequality); behavioral factors (e.g., loss aversion); and political identity.

Among these variables, we find a notable pattern of differential treatment responses along party political lines (Grossman and Helpman 2021): Individuals who identify as Republican supporters display a stronger protectionist reaction to the “Trade Hurts Jobs” narrative, *as well as* to the treatments on gains from being open to trade (for either jobs or prices). On the other hand, in line with the Democratic party being less opposed to trade during the Trump administration, the preference shifts exhibited by its supporters are less intense, *regardless* of whether the evidence conveyed is on the benefits or costs of trade liberalization. As an (unintended) consequence, Republicans and Democrats become even more polarized in their views on trade policy: Our estimates imply that preferences for protection across the two parties’ supporters diverge by about a further one-third of their initial gap following the information treatments. This differential response along party lines is not straightforward to account for through the logic of traditional trade theories. One could argue, for example, that individuals who learn about trade lowering goods prices might favor more protection because they (correctly) infer that some domestic industries are being hurt by import competition; however, it is less clear why Republicans would necessarily be more inclined than Democrats toward this line of reasoning, without referring back to the gap between where the two parties are positioned on trade issues.³

We rationalize these findings instead through a model of belief updating in the formation of trade policy preferences, which accommodates biases in updating that can depend on one’s prior views toward free trade. The model delivers an empirical specification in line with what we explore, calling for interacting the treatment dummies with respondent characteristics that

3. On a related note, we find several other respondent characteristics that are relevant too in mediating how individuals react to narratives on the benefits of trade; we elaborate on these in Section 6.2.

capture these prior beliefs. Through the lens of this framework, our empirical results are consistent with *prior-biased* updating (Charness and Dave 2017, Benjamin 2019): When the received information aligns with the trade policy positions prescribed by one’s political identity, it reinforces these prior preferences. But when the signal is dissonant – such as when a Republican is presented with information that trade yields some benefits – this leads the individual to double down on, rather than move away, from their priors.⁴ It turns out that this doubling down on the part of Republicans is sufficiently strong that it accounts for the average treatment effects – the shift in favor of protection estimated in the overall sample – of the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” narratives.

Finally, we directly canvassed participants who selected “more limits on imports” as a top preferred policy to gauge the specific beliefs behind this choice. Among the reasons listed (including, for example, “not persuaded”, “potential threat to national security”, and “lower quality of imports”), respondents expressed the highest degree of agreement with concerns over how “imports might compete for jobs with U.S. workers” and with “concerns over imports from countries like China” as an explanation for their preference for trade protection. Respondents also used the words “jobs” and “China” with a particularly high frequency in their submitted textual responses. These patterns hold even within the control group, which underscores how the role of China as a trade partner and the impact on jobs loom large as prior concerns in the minds of the American public when the issue of trade is raised (c.f., Mutz 2021); that they hold uniformly too across all treatment groups points further to how persistent these beliefs are, even when dissonant information is conveyed. Of note, these concerns over China and the effects of trade on jobs are more intense among Republican than Democrat supporters, consistent with the two parties’ stances on trade policy during our sample period (2018-2022).

Taken together, our findings highlight key challenges in conveying evidence-based information on the topic of international trade, even though academic economists often adopt this approach when communicating with the general public. We are left to conclude that messaging that focuses solely on portraying the benefits of trade is unlikely to succeed unless it also addresses entrenched prior concerns over U.S.-China economic (and geopolitical) relations, as well as over the potential impact on jobs. We discuss some potential ways forward in our concluding section.

The rest of the paper is organized as follows. Section 2 describes the related literature. Section 3 elaborates on our survey design and implementation, and Section 4 then reports broad patterns in the data we collected. Section 5 presents the evidence on the information treatment effects, while Section 6 explores explanations and mechanisms. Section 7 concludes.

2 Related Literature

Our paper lies at the intersection of two lines of work: the literature in international trade on preferences over trade policy (see Baldwin 1989 and Rodrik 1995 for overviews), and the more

4. Such prior-biasedness in how individuals update their views has been found in other settings; see Soroka (2006) on reactions to information about the state of the economy; Nyhan and Reifler (2010), Nyhan et al. (2020), and Barrera et al. (2020) on responses to fact-checking; and Chopra et al. (2022) in the demand for news.

recent body of survey-based studies examining the role of information in shaping views and support on various policy issues (see Haaland et al. 2023 and Stantcheva 2023).

We seek first and foremost to contribute to the literature on the determinants of trade policy preferences at the individual level. We follow Baldwin (1989) in organizing these into two broad sets of explanations that pertain to: economic self-interest and non-economic concerns.⁵ The former considers these preferences to be principally shaped by how one’s personal economic circumstances are affected by openness to trade. Theory points to how this can occur through one’s industry of work (as in the specific-factors or Ricardo-Viner model), or through one’s skill or education level (as in the Heckscher-Ohlin model); these hypotheses have been tested in a body of empirical studies using extant surveys of socioeconomic attitudes.⁶ The more recent work on the “China trade shock”, exemplified by Autor et al. (2013), has further placed the spotlight on geographic location as a locus of economic exposure to trade, as worker mobility across regions is often limited.⁷

The literature has also given consideration to non-economic channels in the formation of trade policy preferences, drawing on insights from political science and behavioral psychology. The role of social and national concerns has been highlighted by Mansfield and Mutz (2009) and Mutz (2021), who find that trade attitudes are often more strongly correlated with individuals’ perceptions of how the country as a whole has been affected by trade, rather than by one’s private financial situation.⁸ On behavioral factors, loss aversion (Kahneman and Tversky 1979, 1984) can induce an anti-trade policy bent, if the perceived utility from the gains from trade is outweighed by the disutility from losses incurred (Freund and Ozden 2008, Tovar 2009).⁹ Separately, Grossman and Helpman (2021) analyze how the social identity that individuals bear – “concerns for members of those groups in society with whom they identify” – can influence their preferred trade policies. As political affiliation now stands as a key source of social identity in many countries (Bonomi et al. 2021, Gennaioli and Tabellini 2023), the party that one supports is in practice a reliable marker of preferences for protection.¹⁰

5. Another branch of the literature has focused on the role of lobbying and interest groups in shaping the “demand-side” of trade policy; see Grossman and Helpman (1995), Krishna (1998), Ornelas (2005), Bombardini (2008), Blanga-Gubbay et al. (2022), Adão et al. (2023), among others.

6. See, for example, Balistreri (1987), Scheve and Slaughter (2001a), O’Rourke and Sinnott (2001), Beaulieu (2002ab), Mayda and Rodrik (2005), Blonigen (2011), Blonigen and McGrew (2014), Jäkel and Smolka (2017), and Mendez and van Patten (2022). There is a parallel literature on the role of personal economic circumstances in shaping preferences over migration policy; see Scheve and Slaughter (2001b), Mayda (2006), Facchini and Mayda (2008, 2009), and Mayda et al. (2022).

7. That said, there are efforts to seek a more comprehensive assessment of how individuals’ economic interests have been affected on net by trade liberalization with China. For example, cheaper inputs from China have enabled U.S. manufacturing firms to become more competitive (Amiti et al. 2017); employment has grown in non-manufacturing sectors in which the U.S. has comparative advantage (Caliendo et al. 2019); U.S. consumers have also experienced gains as a result of the lower prices of Chinese goods (Bai and Stumpner 2019).

8. Rotemberg (2003) develops a theory of trade policy determination in the presence of voter altruism toward other citizens.

9. More subtly, opposition toward free trade could also be driven by uncertainty over the distribution of gains versus losses from adopting such a policy (Fernandez and Rodrik 1991).

10. A related body of work has studied whether trade policy shapes aggregate voting outcomes: see Autor et al. (2020), Fetzer and Schwarz (2021), Lake and Nie (2021), Choi et al. (2021), Che et al. (2022), Blanchard et al. (2022) on the U.S.; Colantone and Stanig (2018) on Brexit; Dippel et al. (2022) on Germany; and Ogeda et

For the most part though, the above literature has (implicitly) assumed a full-information environment. An exception is Ponzetto et al. (2020), who examine support for protection in a setting with costly information acquisition, but work on this topic is otherwise quite limited. Our paper instead places the role of information – specifically, exposure to evidence on the gains and losses from trade – front and center, to explore how this can shift beliefs about trade and preferences over trade policies.

In terms of methodology, we draw on an influential body of work investigating the role of information provision in shaping policy views. Survey-based experiments have been applied to study attitudes toward inequality (Norton and Ariely 2011, Chow and Galak 2012), support for taxes and redistribution (Kuziemko et al. 2015, Alesina et al. 2018, Fisman et al. 2020, Alesina et al. 2023), as well as immigration policy (Haaland and Roth 2020, Grigorieff et al. 2020, Facchini et al. 2022). This has yielded rich and nuanced evidence on the ability of information treatments to move preferences. For example, Kuziemko et al. (2015) find that support for tax and redistribution policies is unaffected when individuals are made aware of the severity of income inequality, a result they attribute to individuals’ lack of trust in government. On the other hand, Alesina et al. (2018) show that information on the degree of intergenerational (im)mobility raises support for some redistribution policies, but only among left-leaning respondents.

A number of survey experiments have been run on topics related to trade and thus speak closely to our paper. Di Tella and Rodrik (2020) provide treatments consisting of scenarios about job losses in a fictional manufacturing plant; they find that participants’ preferences over remedial policies vary depending on whether the losses are attributed in the treatment to demand shocks, technology, bad management, or trade exposure, with the trade exposure treatment in particular inducing support for protection. Several studies including Hiscox (2006), Rho and Tomz (2017), Rodriguez et al. (2021), and Coppock (2022) experiment with issue framing – short cues on gains and/or losses associated with trade incorporated in the question wording – to examine if this shifts views on trade openness.¹¹ Stantcheva (2022) uses surveys to elicit respondents’ knowledge of trade; a key finding is that participants’ beliefs about the efficacy of compensatory redistribution are associated with more support for trade.

Instead of administering hypothetical scenarios or question frames, we provide information that is in principle factual on the documented gains and losses from trade, presenting this in a format that resembles how researchers might communicate their findings to the general public, say on Twitter.¹² Another point of distinction lies in the backfire effect to content about trade that we obtain: While the above prior work has found that cues about the employment losses from trade can reduce support for free trade, they typically find that cues about the consumption gains

al. (2021) on Brazil. On the other hand, Conconi et al. (2014) present evidence that the proximity of elections shapes the trade policy platforms that U.S. politicians adopt.

11. For example, the positive frame question adopted by Rodriguez et al. (2021) in their survey run across Latinobarometro countries is: “Are you in favor of or against (your country) increasing trade with other countries so that prices fall and the variety of products you may buy increases?” Separately, Nguyen (2017) explores whether the Kuziemko et al. (2015) prime on income inequality can affect trade policy preferences.

12. This focus on information that is evidence- or research-based is in the same spirit as a body of experimental studies that have explored whether such findings can prompt the adoption of specific policies by policymakers (Hjort et al. 2021, Vivalt and Coville 2023, DellaVigna et al. 2023).

exert no significant effect on these preferences. The former finding dovetails with our treatment effect for the “Trade Hurts Jobs” narrative, but our results with the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments go further, as information on the benefits of trade delivered in this format even provokes a protectionist reaction. Moreover, by exploring an array of potential mechanisms, our analysis uncovers the important role of individuals’ political identity – Republicans versus Democrats in the context of the U.S. – in mediating how trade policy preferences respond to information, a point not emphasized in this prior work.

3 Survey Design: Methodology and Instrument

We developed a survey with randomized information treatments, that each offer an evidence-based narrative on the gains or losses that stem from trade liberalization. We engaged a professional company (Qualtrics) to administer the survey to a sample representative of the U.S. general population along five dimensions: age, gender, race, education, and region.¹³ The survey consists of four main parts:

Part 1: Background. This first section gathers general biographic characteristics, including: age, gender, ethnicity, country of birth, state of residence, education, employment status (and sector), and household income. In addition, we elicit respondents’ baseline beliefs on a range of economic and socio-political issues, such as their: degree of trust in government; satisfaction with the health of the U.S. job market; willingness to pay more for a U.S. brand of similar quality; outlook for the next generation (how much they agree with the statement that “children born into my community will have a better life than my generation”); assessment of the impact that NAFTA has had on their family (“extremely good” to “extremely bad”); and views on how big of a problem inequality is in the U.S. today (“not a problem” to “a serious problem”). The NAFTA question, in particular, helps to pick up the nature of respondents’ prior experiences and exposure to the effects of trade. In the most recent 2022 round, we also seek their views on how big of a problem inflation is in the U.S. today.

As a marker of respondents’ political identity, we ask which party’s candidate they supported in the most recent presidential election (“Democrat”, “Republican”, or “Neither”). We also gauge the degree of loss aversion using a standard approach in the behavioral economics literature (c.f., Kahneman and Tversky 1979, 1984) by asking one’s preferences between receiving a discount and avoiding a surcharge of an equal dollar amount (which we describe in the context of a monthly cellphone bill). Last but not least, we include several questions on news consumption and media use habits. (The full survey can be found in Appendix A. We avoid using terms related to trade policy in this background questions module to minimize the possibility of inadvertently priming responses on preferred policy measures.)

13. The sampling quotas were: (i) by gender, female: 50.8%, male: 49.2%; (ii) by age, 18-24: 12.8%, 25-34: 17.7%, 35-44: 16.7%, 45-54: 17.7%, 55-64: 16.4%, 65+: 18.8%; (iii) by race, non-Hispanic White: 61.9%, non-Hispanic Black: 12.3%, Hispanic: 17.4%, Asian: 5.3%, Other: 3.2%; (iv) by education, HS diploma/GED or less: 40.8%, some college (no degree): 20.9%, college degree: 26.9%, graduate degree: 11.4%; and (v) by region, Midwest: 21.33%, Northeast: 18.02%, South: 37.27%, West: 23.38%. Participants who completed the survey received about \$2 each; the average cost per respondent charged by the company was \$5-\$6 across the rounds. The 2022 survey platform can be accessed at: https://hbs.qualtrics.com/jfe/form/SV_esNIwU1v3V4Iufc.

Part 2: Treatment. Respondents are then randomly allocated with equal probability to the control group (no narrative received) or one of the information treatments. Each narrative starts with the same preamble – “How have globalization and imports affected workers and households? Economic researchers have been studying this issue.” – and proceeds to describe an employment or price effect of openness to trade found to be quantitatively important following China’s accession to the WTO in 2001:

- (a) The “Trade Hurts Jobs” narrative reports the main finding of Autor et al. (2013) on how the rise in imports from China had a negative impact on the labor market outcomes of manufacturing workers in the U.S.
- (b) The “Trade Helps Jobs” narrative relates how the rise in imports from China led the U.S. to specialize more in service sectors as established by Caliendo et al. (2019), which contributed to an increase in the total number of jobs in the U.S. economy.
- (c) The “Trade Helps Prices” narrative describes how the rise in imports from China was accompanied by lower prices for both durable goods (computers, electrical products, furniture) and non-durable goods (apparel), drawing on price indices from the Bureau of Labor Statistics.
- (d) Starting in the 2020 survey and following the resurgence in U.S. import tariffs, we introduced the “Tariff Hurts Prices” narrative based on the findings of Amiti et al. (2019). This describes how the tariffs imposed starting in 2018, particularly on imports from China, resulted in higher prices for tariff-affected goods, incurring an estimated loss to U.S. real income of \$1.4 billion per month.

To make the information accessible, each narrative was limited to three to four sentences that avoid technical jargon, akin to a short social media post.¹⁴ To facilitate respondents who might prefer visual forms of information, each narrative was accompanied by a figure illustrating the key trend over time in either job outcomes or goods prices. In the “Trade Hurts Jobs” treatment, we reproduced Figure 1 from Autor et al. (2013), which overlays the increase in imports from China between 1987-2007 with the contemporaneous decline in the manufacturing employment share in the U.S. population. For the “Trade Helps Jobs” and “Trade Helps Prices” treatments, we created analogous figures in which the decline in manufacturing employment was replaced by data series illustrating respectively the rise in total U.S. nonfarm jobs and the fall in U.S. goods price indices. For the “Tariff Hurts Prices” treatment, we included a figure showing how the U.S. prices of tariff-affected goods rose following the new tariffs in early 2018. It should be stressed that each narrative was crafted based on evidence backed by recent economics research or data, while adopting a neutral and factual tone; we did not deliberately expose participants to falsified or hypothetical accounts. (The narratives and figures are presented in Appendix A.1.)

Apart from the four baseline narratives, we also implemented several variants in later survey editions; these were similarly randomized to a comparable group of participants. Starting in 2020, we ran treatments in which both the “Trade Hurts Jobs” and “Trade Helps Jobs” information were jointly provided, to gauge the impact of these composite treatments and whether this was

14. While the treatment screen includes an academic citation to attribute the source of the narrative, the names of the institutions to which the researchers are affiliated were not included to avoid potential bias that could arise due to reputations or perceptions associated with the institutions.

affected by the order in which the two pieces of information were presented. We also exposed respondents to versions in which we removed key wording – such as taking out explicit mention of “China” and referring instead to a general increase in imports into the U.S. – to assess the sensitivity of our findings. We elaborate on these additional treatments in Section 5.3.¹⁵

Part 3: Policy Preferences. We proceed to solicit preferences over economic policies. We capture preferences for protection through the following directly-posed questions:

- (a) “Do you support placing more limits on import?” (Yes or No.)
- (b) “Would you support an increase in the U.S. tariff rate to reduce imports?” (Yes or No.)
- (c) “Would you support the U.S. signing free trade agreements with more foreign countries?” (Yes or No.)
- (d) “Of the following two policies, which do you prefer?” (Higher taxes on top income earners; Higher tariffs on imports from foreign countries; Both policies; Neither policy.)

We further included a question in which respondents were asked to select their three “Most Preferred” policies from a list of eight options, to gauge the strength of their preference for protection relative to other measures commonly proposed to address labor market concerns. The eight policies are: “higher taxes on top income earners”; “higher minimum wage”; “more benefits for the unemployed (e.g., unemployment insurance)”; “improving education and worker training”; “more limits on imports from foreign countries (e.g., higher tariffs on imports)”; “weakening the U.S. dollar, so that U.S. exports are more competitive”; “exiting from existing free trade agreements”; “more limits on immigration”. These were presented on each participant’s survey screen in a random order to account for possible choice biases that can arise from the order in which the options appear.

The phrasing we adopt in these policy questions is comparable to that in established socio-economic surveys such as the Gallup Poll, American National Elections Studies, and World Values Survey. We ask about trade policy in multiple ways – e.g., “higher tariff rates on imports”, “more limits on imports” – in order to elicit respondents’ broad inclination toward protectionism, and to avoid being overly reliant on any single question. For example, a participant might misread a particular question, or inadvertently select an answer option that was not what they intended. We will later work with a principal component measure that extracts a common component of variation in the answers recorded on these five questions, which will alleviate concerns over such possible measurement error.

Part 4: Validate and Explain Choices. Beginning in 2020, we included a set of questions to validate how well participants engaged with the narratives. We asked directly whether the

15. The debate on whether trade has been the main reason behind stagnated low-skill wages is far from settled. Manufacturing employment has fallen steadily in most developed nations for decades (Lawrence and Lawrence 2012), and a leading alternative hypothesis is that technological change – the rise of computers, automation, and robotics – displaced low-end manufacturing jobs (see Acemoglu and Restrepo 2017). In the 2018-2019 survey, we included a “It’s not Trade, it’s Technology” narrative based on the statement: “Technological advances in recent decades, such as computerization and automation, have tended to favor skilled workers while replacing some jobs that used to be performed by unskilled workers.” The effects were not statistically significant and, given budget constraints, we omitted this from subsequent survey runs to focus on the jobs- and prices-related treatments.

information read earlier in the survey affected their views on trade policy (“strongly disagree” to “strongly agree”). As a basic recall question, we also asked whether the information received was on the topic of “the relationship between trade and jobs” or “the relationship between trade and prices” (with “I did not receive information on any of the above” as the third option).

To elicit the beliefs and concerns that shape protectionist choices, we included starting from the 2021 survey a set of follow-up questions for participants who selected “more limits on imports” as a top-three preferred policy. These respondents were reminded of their policy selection and then asked to assess the degree to which each of the following reasons explained this choice on a scale of 1 (“strongly disagree”) to 5 (“strongly agree”):

- I was persuaded that imports have hurt jobs in the U.S. (for respondents who received “Trade Hurts Jobs”)
- I was not persuaded that trade has helped to create jobs in the U.S. (for “Trade Helps Jobs”)
- I was not persuaded that imports have lowered goods prices for Americans (for “Trade Helps Prices”)
- I was not persuaded that tariffs imposed by the U.S. have raised goods prices for Americans (for “Tariff Hurts Prices”)
- Imports are often of lower quality.
- Imports are a potential threat to U.S. national security.
- Imports often compete for jobs with U.S. workers.
- I am concerned about U.S. imports from countries such as China.
- There are other more important concerns.

The answer options for the basic recall question and the list of reasons for selecting “more limits on imports” in this follow-up question were also presented in random order. Last but not least, these respondents were invited to describe any other relevant reasons in a text box.

We conducted annual runs of the survey over 2018-2022, which we grouped into four rounds. The first surveys were launched in July 2018 and April 2019, with the “Trade Hurts Jobs”, “Trade Helps Jobs”, and “Trade Helps Prices” treatments; we have grouped these two pre-pandemic years as a single “round” due to the smaller number of observations (2,277). The second round was conducted from April-June 2020 on a sample of 6,009 participants; in addition to the same treatments in round 1, we introduced the “Tariff Hurts Prices” narrative related to the new U.S. tariffs. This second round also included the mixed jobs treatments, as well as versions of the “Trade Helps Prices” narrative with modified wording (see Section 5.3). The third round in April 2021 yielded a sample of 4,058 participants, while the fourth round in April-July 2022 delivered 6,005 observations. In total, we have over 18,000 respondents across the four survey rounds. Note that we did not seek to assemble a longitudinal panel of the same individuals over time due to the challenge of low re-contact rates and concerns over potential self-selection into the follow-up sample, as discussed in Stantcheva (2023).

The mean time taken to complete the survey was about 15 minutes in rounds 2-4 after the validation and follow-up questions were added; the distribution of completion times is right-

skewed, with a median of around 11 minutes (see the bottom of Table 1).¹⁶ Within the survey, respondents spent about half a minute on average on the information treatment screens.¹⁷ With the information collected on the state of residence and the name of one’s city or town, we could infer the county of residence for most respondents. This allowed us to merge in a set of location characteristics drawn from standard sources of U.S. county-level data for more than 96% of the observations in each survey round.¹⁸

4 Broad Patterns of Policy Preferences

We provide a first look at our data and describe several key patterns. Table 1 reports summary statistics from the four survey rounds, on a range of biographic variables (e.g., gender, age), socio-economic characteristics (e.g., household income, education, employment), political identity (party supported in the last presidential election), and news consumption patterns (e.g., media sources, frequency). We also tabulate these for several location characteristics, which respondents would, in principle, be exposed to through their county of residence; these are: the college-educated share (from the American Community Survey), the manufacturing share in local employment (County Business Patterns dataset), exposure to imports from China for 2000-2007 (Autor et al. 2013), and whether the location is an urban area (US Census).¹⁹

Looking across the columns in Table 1, the means of the respondent and location characteristics are similar over the survey rounds. The profile of our sample along the gender, age, race, and education dimensions are by construction consistent with the distributions in the U.S. general population. We also match fairly well the labor force participation rate (e.g., 61% in round 4), as well as employment shares by sector (e.g., $0.07/0.51 \approx 13.7\%$ for manufacturing and $0.40/0.51 \approx 78.4\%$ for services in round 4), even though these moments are not explicitly targeted.²⁰ On the other hand, the sample slightly over-represents the unemployment rate (10-11% across rounds), while leaning more Democrat in terms of left-right political identity (41-49% Democrat versus 34-36% Republican support). This *per se* does not invalidate our empirical approach, since we

16. As a data quality measure, Qualtrics removed observations that took less than half the median completion time after a first run of collection and replaced these with freshly sampled respondents to fulfill the requested survey quotas.

17. Round 1 saw a longer average duration on the treatment screen, as the preamble of the narratives included more background information on inequality trends in the U.S.; this was removed in rounds 2-4.

18. We performed a fuzzy merge with a repository of city names across U.S. states. Observations with a Stata `reclink` fuzzy merge score lower than 0.93 were checked manually to correct for spelling errors, the use of abbreviations (e.g., “St.” versus “Saint”), and differences between colloquial and formal names (e.g., “St. Pete” versus “St. Petersburg”). Where there was potential ambiguity, the IP address coordinates of the respondents were geolocated using Google Maps to determine their likely location. We dropped respondents with coordinates located outside the U.S.; these comprised less than 0.3% of the entire sample.

19. The college-educated variable is expressed as a share of the local population aged 25 and older, and is a five-year average over 2013-2017. The manufacturing share variable is for the year 2016. Both measures are constructed at the county level, whereas the China import shock variable taken from Autor et al. (2013) is at the commuting zone level. The urban area definition is from 2010.

20. For comparison, the labor force participation rate reported for 2022 by the U.S. Bureau of Labor Statistics is around 62%. The manufacturing and services shares of employed workers calculated from the 2022 Current Population Survey are 9.6% and 76.3%, respectively.

Table 1: Summary Statistics: Respondent Characteristics by Survey Round

	Round 1 2018-19 (N=2,277)	Round 2 2020 (N=6,009)	Round 3 2021 (N=4,058)	Round 4 2022 (N=6,005)
Biodata				
Gender: Male	0.49 [0.50]	0.47 [0.50]	0.49 [0.50]	0.48 [0.50]
Gender: Female	0.51 [0.50]	0.52 [0.50]	0.51 [0.50]	0.52 [0.50]
Age: Average (approx.)	47.55 [16.78]	45.45 [16.61]	46.55 [16.69]	46.45 [16.78]
Race: White	0.61 [0.49]	0.67 [0.47]	0.62 [0.48]	0.62 [0.49]
Race: African-American	0.11 [0.32]	0.13 [0.33]	0.12 [0.32]	0.12 [0.33]
Race: Hispanic	0.17 [0.37]	0.13 [0.34]	0.18 [0.38]	0.17 [0.38]
Born in US?	0.92 [0.27]	0.92 [0.27]	0.91 [0.28]	0.92 [0.28]
Socio-Economic Characteristics				
Household Income: Average \$ (approx.)	58,196 [47,585]	64,886 [54,093]	62,010 [49,462]	58,785 [45,827]
Education: Average years (approx.)	11.81 [4.91]	11.56 [4.86]	11.71 [4.87]	11.70 [4.86]
Employment Status: Not in Labor Force	0.40 [0.49]	0.39 [0.49]	0.39 [0.49]	0.39 [0.49]
Employment Status: Unemployed	0.10 [0.30]	0.11 [0.32]	0.10 [0.30]	0.10 [0.30]
Employment Status: Employed	0.50 [0.50]	0.50 [0.50]	0.50 [0.50]	0.51 [0.50]
Employment Sector: Manufacturing	0.08 [0.26]	0.09 [0.28]	0.07 [0.26]	0.07 [0.26]
Employment Sector: Services	0.39 [0.49]	0.36 [0.48]	0.39 [0.49]	0.40 [0.49]
Student?	0.03 [0.17]	0.04 [0.20]	0.04 [0.20]	0.03 [0.17]
Loss aversion (Scale: 1 to 5)	—	3.11 [1.47]	3.07 [1.50]	3.06 [1.50]
Baseline Socio-Political Attributes				
Last Presidential election: Supported Dem.	0.41 [0.49]	0.41 [0.49]	0.49 [0.50]	0.44 [0.50]
Last Presidential election: Supported Rep.	0.34 [0.47]	0.36 [0.48]	0.33 [0.47]	0.34 [0.47]
Trust in government? (Scale: 1 to 5)	2.50 [1.05]	2.79 [1.13]	2.69 [1.11]	2.55 [1.08]
Impact of NAFTA on family (Scale: 1 to 5)	3.16 [0.90]	3.35 [0.90]	3.31 [0.87]	3.11 [0.91]
Children born into better life? (Scale: 1 to 5)	3.07 [1.13]	3.23 [1.10]	3.16 [1.15]	2.95 [1.14]
Satisfied with health of US job market?	0.48 [0.50]	0.35 [0.48]	0.40 [0.49]	0.41 [0.49]
Willing to pay more for US brand?	0.59 [0.49]	0.65 [0.48]	0.63 [0.48]	0.61 [0.49]
Inequality in US a problem? (Scale: 1 to 4)	3.01 [0.96]	2.96 [0.95]	2.97 [0.96]	2.99 [0.94]
Inflation in US a problem? (Scale: 1 to 4)	—	—	—	3.42 [0.80]
News consumption patterns				
Number of days per week (approx.)	5.02 [2.47]	5.29 [2.34]	5.01 [2.43]	4.87 [2.52]
Main tv source: Broadcast tv	0.29 [0.45]	0.26 [0.44]	0.25 [0.43]	0.26 [0.44]
Main tv source: CNN, MSNBC	0.17 [0.37]	0.21 [0.40]	0.20 [0.40]	0.16 [0.37]
Main tv source: Fox News	0.16 [0.36]	0.17 [0.38]	0.15 [0.36]	0.16 [0.37]
Location Characteristics				
Share with college and above (age \geq 25)	0.30 [0.11]	0.31 [0.12]	0.31 [0.11]	0.30 [0.10]
Autor-Dorn-Hanson measure for 2000s	2.56 [1.82]	2.57 [2.11]	2.54 [1.77]	2.61 [2.02]
Share of manufacturing in employment	0.16 [0.11]	0.16 [0.11]	0.16 [0.11]	0.16 [0.11]
Urban?	0.86 [0.35]	0.87 [0.33]	0.86 [0.35]	0.85 [0.35]
Survey Characteristics				
Duration to complete (secs.)	727 [1,513]	912 [2,292]	888 [1,015]	897 [925]
Treatment duration	47 [66]	28 [84]	28 [58]	26 [64]
Mobile device?	0.61 [0.49]	0.70 [0.46]	0.58 [0.49]	0.54 [0.50]

Notes: Mean values reported, with standard deviations in brackets. For respondent age, household income, and frequency of news consumption, this is approximated by a weighted average of the midpoint values of the response option bins, using the share of respondents picking each bin as weights. For respondent years of education, an analogous weighted average is taken that assigns 6 years to “High school or less”, 14 years to “Some college”, 16 years to “College graduate”, and 18 years to “Post graduate”. The average treatment duration is longer in Round 1 due to a longer treatment preamble (which was shortened in later rounds).

will show that the control and treatment groups within each round are balanced across these key characteristics.

It is worth highlighting several interesting patterns in socio-political attitudes. The average respondent exhibited a slight distrust in government, held mildly negative views of the impact of NAFTA and on the health of the U.S. job market (especially in rounds that coincided with the Covid-19 pandemic), and expressed a slight willingness to pay more for U.S. brands. Respondents also viewed both inequality and inflation as a problem, particularly inflation in 2022. That said, there is substantial dispersion in each of these variables around their respective means.

Turning to policy preferences, Table 2 (top panel) presents the declared support for various policies – including trade-related policies – when these are elicited in a directly-posed “Yes/No” format; we report unconditional means here pooling across the control and all treatment groups. When queried in this “Yes/No” manner, a fairly large share of respondents agreed with placing more limits on imports (57-62% across the four rounds). At the same time, the share favoring alternative policies, such as a minimum wage and more progressive taxation (“higher taxes on top income earners”), was similarly high (65-80%).²¹ Interestingly, between 65-68% of the participants indicated support for signing new free trade agreements; it is possible that some respondents may not see limits on imports and more free trade agreements as contradictory, since these moves could be pursued with different foreign countries.

The lower panel in Table 2 summarizes the responses to the “Most Preferred” policy question, where participants selected their top three policies from the menu of eight options. The share of respondents who selected “more limits on imports” was between 23-28%, while only around 12% identified “exiting from free trade agreements” as a preferred course of action. Put otherwise, import restrictions received less support once individuals were asked to prioritize this against other policies, as seen from the distinct gap to the 57-62% who agreed with “more limits on imports” when this was posed as a “Yes/No” question. On the other hand, tax or labor market measures – “improve education and training”, a “higher minimum wage”, and “higher taxes on top income earners” – each received broad support, from about 50-60% of those surveyed. Not all public assistance programs were favored though, as only about a quarter of respondents selected “more unemployment benefits”. “More limits on immigration” received a measure of support (34-37%), while the option with the least backing was to “weaken the US Dollar” (7-9%).²²

The ranking of support for the eight policy options was similar across the survey rounds. A “higher minimum wage” was consistently selected as a “Most Preferred” policy by the largest share of respondents, followed by “improve education and worker training” and “higher taxes on top income earners”. There appears to be an uptick over time in the share supporting “more

21. The sum of the shares for “Prefer: Higher tariff rates on foreign countries?” and “Prefer: More progressive taxes?” exceeds one, since respondents were allowed to select “Both” in this survey question. The share who selected “Prefer: Higher tariff rates on foreign countries?” also exceeds the share who replied yes on “Would you support an increase in the U.S. tariff rate?” For the latter question, one of the response options was to keep the tariff rate the same, and a majority of respondents (around 60%) appear to have gravitated to this as a default answer. That said, respondents who expressed support for higher tariffs on one of these questions were also likely to do so on the other (correlation coefficient: 0.27, across all rounds).

22. The responses to the complementary question on one’s “Least Preferred” policies yielded a consistent message, with “improve education and training”, “higher minimum wage”, and “higher taxes on top income earners” selected with the lowest frequencies (details available on request).

Table 2: Expressed Policy Preferences: Respondent Shares

	Round 1	Round 2	Round 3	Round 4
	2018-19	2020	2021	2022
	(N=2,277)	(N=6,009)	(N=4,058)	(N=6,005)
Do you support placing more limits on imports?	0.57 [0.49]	0.62 [0.49]	0.59 [0.49]	0.58 [0.49]
Would you support an increase in the US tariff rate?	0.28 [0.45]	0.25 [0.43]	0.25 [0.43]	0.32 [0.47]
Prefer: Higher tariff rates on foreign countries?	0.44 [0.50]	0.50 [0.50]	0.47 [0.50]	0.48 [0.50]
Prefer: More progressive taxes?	0.68 [0.46]	0.65 [0.48]	0.68 [0.47]	0.68 [0.47]
Would you support signing more FTAs?	0.68 [0.47]	0.65 [0.48]	0.65 [0.48]	0.64 [0.48]
Would you support a minimum wage?	0.78 [0.41]	0.80 [0.40]	0.74 [0.44]	0.78 [0.42]
Most Preferred Policies (pick 3 out of 8)				
More limits on foreign imports	0.23 [0.42]	0.27 [0.44]	0.28 [0.45]	0.28 [0.45]
Exiting from FTAs	0.13 [0.34]	0.12 [0.33]	0.13 [0.34]	0.12 [0.33]
More limits on immigration	0.34 [0.47]	0.31 [0.46]	0.37 [0.48]	0.35 [0.48]
Weaken the USD	0.07 [0.26]	0.09 [0.29]	0.09 [0.28]	0.08 [0.28]
Higher taxes on top income earners	0.51 [0.50]	0.46 [0.50]	0.50 [0.50]	0.53 [0.50]
Higher minimum wage	0.61 [0.49]	0.60 [0.49]	0.56 [0.50]	0.61 [0.49]
More unemployment benefits	0.30 [0.46]	0.34 [0.47]	0.29 [0.45]	0.30 [0.46]
Improve education and worker training	0.59 [0.49]	0.49 [0.50]	0.52 [0.50]	0.56 [0.50]

Notes: Values reported are equal to the share of respondents pooled across the control and all treatment groups, who expressed a preference for the policy in question; standard deviations are in brackets. The shares for “Prefer: Higher tariff rates on foreign countries?” and “Prefer: More progressive taxes?” do not sum to one, as respondents were allowed to select both policies.

limits on imports” as a “Most Preferred” policy – from 23% in 2018-2019, to 27-28% in 2020-2022 – though this pattern is not uniformly replicated; in the direct “Yes/No” question, the share of respondents who favored more limits on imports peaks instead in round 2.²³

5 Evidence on Information Treatment Effects

5.1 Empirical Specification

We turn to the task of identifying whether and how the information treatments affected policy preferences. We evaluate this formally using the following regression specification:

$$\mathbf{1}(Policy_i) = \sum_{b=1}^B \beta_b \mathbf{1}(Treatment_i = b) + \gamma X_i + \epsilon_i, \quad (1)$$

where $\mathbf{1}(Policy_i)$ is an indicator variable for whether respondent i expressed support for the particular policy measure. The $\mathbf{1}(Treatment_i = b)$ ’s are each dummy variables that take on the value of one if the respondent received information treatment b ; the omitted category ($b = 0$) is the no-information control group. The β_b coefficients (for $b = 1, \dots, B$) therefore capture the effects of the respective treatments relative to the control; given the randomization of treatments to respondents, these can be accorded a causal interpretation. In Appendix Tables 1a-1e, we

23. The variation in these preferences across regions of the U.S. is broadly consistent with the well-known geographic divisions in support for the Republican versus Democratic party (available on request).

confirm that within each survey round, the randomization achieved balance in a large set of respondent characteristics across the control and treatment groups.²⁴

We include in (1) a vector X_i of controls. This includes: (i) biographic variables (gender, age group, race, education, employment status and sector, household income, region of birth); (ii) prior political identity (based on the party supported in the most recent presidential election); and (iii) news consumption habits (frequency, main sources). To capture the preceding variables flexibly, we control for each using a set of dummies for the response options from the associated survey question. We further control in X_i for: (iv) several location-specific socioeconomic conditions (as described earlier, the college-educated share, manufacturing share in employment, exposure to imports from China, an urban dummy). The underlying randomization implies that the assignment of treatments should be orthogonal with respondent or location characteristics, and so the inclusion of X_i is in principle not crucial for the consistency of the treatment effects. Indeed, the β_b 's that we estimate with and without the set of controls are similar (see Appendix Table 2). The main purpose of including these covariates is instead to facilitate a comparison with the prior empirical literature on the correlates of preferences for trade protection.

Last but not least, we account for several survey features. When the outcome is whether “more limits on imports” was selected as a “Most Preferred” policy, we control for the “randomization order”, i.e., the position (1 to 8) of “more limits on imports” in the list presented to respondent i ; as we will see, this typically has a negative coefficient, which points to the usefulness of accounting for the tendency among some respondents to pick options that appear earlier on their screen. We also include survey week dummies (to capture the effects of contemporaneous events), and for whether the survey was taken on a mobile device (to control for possible differences in how mobile and non-mobile users might process information).²⁵

We run logit regressions based on (1), using in turn the following dependent variables for $\mathbf{1}(Policy_i)$: (i) whether a “Yes” answer was recorded for “Do you support placing more limits on imports?”; (ii) whether a “Yes” was recorded for “Would you support an increase in the U.S. tariff rate?”; (iii) whether “higher tariffs on imports from foreign countries” or “both” (higher tariffs and higher taxes on top income earners) was selected on the question on preferences over these two policies; (iv) whether a “Yes” was recorded for “Would you support signing more free trade agreements?”; and (v) whether “more limits on imports” was chosen as a top-three “Most Preferred” policy. For these logit regressions, we report marginal effects that are evaluated setting the treatment dummies, $\mathbf{1}(Treatment_i = b)$, at a baseline value of zero and the covariates in X_i to their in-sample mean values.

In addition, we will run OLS regressions based on the specification in (1), in which we use the

24. The randomization-t p-value (c.f., Young 2019) for a multiple hypothesis test of the orthogonality of the listed covariates in the appendix tables is 0.864, 0.019, 0.509, and 0.438, respectively, for rounds 1-4 (with 1,000 iterations, controlling for survey-week fixed effects). In the two variants of the “Trade Helps Prices” narrative included in round 2, which removed “China” and “cheaper” respectively from the wording, the profile of these respondent groups was older and had slightly fewer years of education (Appendix Table 1b, last two columns); if these two characteristics are dropped, we do not reject the null hypothesis of orthogonality in this round (p-value=0.546). We take care to condition on age and education in the regression analysis.

25. Over half the respondents completed the survey on a mobile device (Table 1). See Couper et al. (2017) for a review of potential concerns that arise with mobile web-based surveys.

first principal component of (i)-(v) as the dependent variable. We subtract the binary response to (iv) – “Would you support signing more free trade agreements?” – from one prior to computing this principal component, so that the measure is increasing in the intensity of preferences for protection. The pairwise correlation across (i)-(v) constructed as such ranges between 0.103-0.367 (pooling across all survey rounds), indicating that while expressions of protectionist preferences are broadly aligned across the individual questions, this correlation is far from perfect; to the extent that this arises from measurement error on any single survey question, using the first principal component will in principle dampen the impact of such noise.

5.2 Effects of Baseline Treatments

We analyze the effects of the information treatments, comparing the results from round 1 (2018-2019, pre-Covid) against those from the subsequent rounds 2-4 (2020-2022, Covid and after). We report standard errors clustered by county of residence throughout the regression tables.

Baseline round (2018-2019). Table 3 presents the round 1 results. Participants who received the “Trade Hurts Jobs” treatment exhibited significantly stronger preferences for protection relative to the control group. For the five trade policy questions (i)-(v), exposure to this evidence on how trade led to manufacturing job losses raises support for “more limits on imports” (Column 1, the “Yes/No” question), a “U.S. tariff rate increase” (Column 2), and “higher tariffs” (Column 3, when juxtaposed with “higher taxes on top income earners”); this treatment group was also more likely to pick “more limits on imports” as a top-three “Most Preferred” policy (Column 5). At the same time, this narrative lowers support for free trade agreements, although this effect falls short of statistical significance (Column 4). Overall, we find when using the first principal component measure that individuals exposed to the “Trade Hurts Jobs” information display stronger support for protection (Column 6). The “Trade Hurts Jobs” coefficient of 0.282 in this last column implies a treatment effect which is about one-third of the average gap between Republicans and independents in their degree of support for protectionist measures; as an alternative benchmark, this effect is about one-fifth the size of a standard deviation in the principal component measure of the intensity of protectionist preferences (1.400).

In contrast, communicating evidence that “Trade Helps Jobs” did not shift trade policy preferences in a statistically significant way, although the point estimates in several of the columns (including for the principal component measure) suggest that this narrative mildly tips respondents in a protectionist direction. On the other hand, the “Trade Helps Prices” narrative yields striking results: when presented with evidence showing that imports have been associated with lower goods prices, participants *raise* their support for more limits on imports (Columns 1 and 5), and for higher tariffs (Column 3). With the first principal component measure (Column 6), the “Trade Helps Prices” treatment effect is significant at the 5% level, with a slightly smaller magnitude compared to the effect of exposure to the “Trade Hurts Jobs” narrative. Somewhat surprisingly (and even paradoxically), it appears that evidence-based information on the impacts of trade can trigger increased preferences for trade protection, regardless of the positive or negative nature of the impact presented.

Later rounds (2020-2022). Prompted by the results from round 1, we conducted annual runs

Table 3: Effect of Information Treatments on Preferences Towards Trade Policy
(Round 1, 2018-2019)

	(1)	(2)	(3)	(4)	(5)	(6)
Trade Policy Qns	More limits on imports	US tariff increase	Support higher tariff	Support more FTAs	Most Pref.: More limits on imports	First prin. component
	Logit	Logit	Logit	Logit	Logit	OLS
<u>Treatment Dummies:</u>						
Trade Hurts Jobs	0.060* [0.032]	0.045* [0.026]	0.083*** [0.032]	-0.046 [0.030]	0.080*** [0.024]	0.282*** [0.076]
Trade Helps Jobs	0.007 [0.035]	0.033 [0.034]	0.064 [0.041]	0.017 [0.032]	0.040 [0.027]	0.135 [0.098]
Trade Helps Prices	0.057* [0.034]	0.018 [0.030]	0.071* [0.039]	-0.007 [0.032]	0.069** [0.028]	0.211** [0.089]
Randomization Order				-0.003 [0.003]	0.003 [0.011]	
Supported Democrat	-0.042 [0.029]	-0.043* [0.022]	-0.043 [0.026]	0.091*** [0.027]	-0.064*** [0.019]	-0.259*** [0.075]
Supported Republican	0.224*** [0.030]	0.147*** [0.028]	0.219*** [0.029]	-0.034 [0.029]	0.092*** [0.023]	0.728*** [0.081]
Individual, County, Week Controls?	Y	Y	Y	Y	Y	Y
Observations	2,277	2,277	2,277	2,277	2,277	2,277
(Pseudo) R-squared	0.0970	0.103	0.0742	0.0746	0.0783	0.183

Notes: Based on the Round 1 (2018-2019) sample; comprising respondents in the “Control” group who received no information treatment (the omitted category), as well as those who received the “Trade Hurts Jobs”, “Trade Helps Jobs” and “Trade Helps Prices” treatments. The dependent variable in Columns 1-4 is an indicator equal to 1 if the respondent indicated support for the policy in a directly-posed question; that in Column 5 is an indicator equal to 1 if the respondent identified “More limits on imports” among his/her three “Most preferred” out of the list of eight policies; while that in Column 6 is the first principal component constructed to be increasing in preferences for more limits on trade. The controls included (but not reported) are: individual dummies for gender, age group, race, level of studies, household income bins, employment status (including broad sector), survey answered on a mobile device, BEA region of birth (including foreign-born category), frequency following current affairs, and news program source; county controls for share of college-educated, ADH exposure to China imports (2000-2007), manufacturing share of employment, urban dummy, missing county information dummy; survey response week dummies. The “Randomization Order” variable is the list order in which “More Limits on Imports” was presented among the eight policy options to the respondent in question. Columns 1-5 report marginal effects from logit regressions, evaluated with the treatment dummies at a base value of zero, while setting all other right-hand side controls at their in-sample mean values. Column 6 reports an OLS regression. Standard errors are clustered by respondent county and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5%, and 10% levels respectively.

of the survey between 2020-2022 to explore the robustness of the initial findings, as well as to probe deeper into explanations for these patterns. As described in Section 3, the core survey remained unchanged, even as we progressively added several treatment narratives and follow-up questions. Table 4 reports on the estimates from these later rounds. The regressions here pool the observations across rounds 2-4, since we obtain qualitatively similar results when examining each round separately (albeit with slightly less precision, see Appendix Table 3).

We find that the key results documented in 2018-2019 continue to hold in 2020-2022. Once again, the “Trade Hurts Jobs” treatment exerts a particularly noticeable effect: it raises respondents’ propensity to favor protection uniformly across all the policy preference variables we

Table 4: Effect of Information Treatments on Preferences Towards Trade Policy
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade Policy Qns	More limits on imports	US tariff increase	Support higher tariff	Support more FTAs	Most Pref.: More limits on imports	First prin. component	Did info affect views?	Impact of trade on Americans
	Logit	Logit	Logit	Logit	Logit	OLS	Ord. Logit	Ord. Logit
Treatment Dummies:								
Trade Hurts Jobs	0.091*** [0.017]	0.071*** [0.015]	0.036** [0.017]	-0.038** [0.018]	0.033** [0.015]	0.242*** [0.043]	0.048*** [0.015]	-0.248*** [0.016]
Trade Helps Jobs	0.023 [0.018]	0.023 [0.015]	0.026 [0.018]	-0.006 [0.019]	0.009 [0.015]	0.081* [0.044]	0.030* [0.016]	-0.025* [0.015]
Trade Helps Prices	0.057*** [0.017]	0.027* [0.014]	-0.005 [0.017]	-0.001 [0.017]	0.031** [0.015]	0.109*** [0.042]	0.028* [0.015]	-0.058*** [0.015]
Tariff Hurts Prices	0.040** [0.017]	0.020 [0.014]	0.017 [0.017]	-0.004 [0.017]	0.023 [0.016]	0.099** [0.042]	0.046*** [0.016]	-0.164*** [0.016]
Randomization Order				-0.011*** [0.002]	-0.019*** [0.006]			
Supported Democrat	0.003 [0.014]	0.006 [0.011]	-0.042*** [0.016]	0.124*** [0.014]	-0.040*** [0.012]	-0.141*** [0.035]	0.093*** [0.013]	0.089*** [0.012]
Supported Republican	0.193*** [0.016]	0.122*** [0.013]	0.143*** [0.015]	-0.037** [0.015]	0.141*** [0.015]	0.625*** [0.040]	0.084*** [0.013]	-0.002 [0.013]
Individual, County, Week Controls?	Y	Y	Y	Y	Y	Y	Y	Y
Observations	9,275	9,275	9,275	9,275	9,275	9,275	9,275	9,275
(Pseudo) R-squared	0.0766	0.0801	0.0471	0.0698	0.0796	0.153	0.0488	0.0569

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the “Control” group who received no information treatment (the omitted category), as well as those who received the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments. The dependent variable in Columns 1-4 is an indicator equal to 1 if the respondent indicated support for the policy in a directly posed question; that in Column 5 is an indicator equal to 1 if the respondent identified “More limits on imports” among his/her three “Most preferred” out of the list of eight policies; that in Column 6 is the first principal component constructed to be increasing in preferences for more limits on trade; that in Column 7 is a categorical variable for the degree of agreement with the statement that the information received affected one’s views on trade policy (1=“Strongly disagree”, 5=“Strongly agree”); while that in Column 8 is a categorical variable asked post-treatment on views on the impact that trade has had for most Americans (1=“Extremely bad”, 5=“Extremely good”). The controls included (but not reported) are as listed in the Table 3 footnotes. Columns 1-5 report marginal effects from logit regressions; Columns 7 and 8 report marginal effects from ordered logit regressions on the predicted probability that either the fourth or fifth highest ordered category is selected as the response. All marginal effects are evaluated with the treatment dummies at a zero base value, while all other right-hand side controls are set at their in-sample mean values. Column 6 reports an OLS regression. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5%, and 10% levels respectively.

consider (Columns 1-6, Table 4). As for the “Trade Helps Jobs” narrative, we obtain a positive and significant effect at the 10% level with the first principal component outcome measure (Column 6); the implied magnitude of the shift in favor of import protection is about one-quarter that of the “Trade Hurts Jobs” treatment. If anything then, this mode of communicating that trade has some beneficial labor market effects tilts respondents towards more protectionist preferences. (As we will shortly see, this result persists even among respondents who could correctly recall that this information treatment was on the topic of jobs; see Table 6.)

For the price-related effects of trade, we replicate the puzzling finding from Table 3. The “Trade Helps Prices” narrative significantly raises support for protection, albeit with a treatment coefficient about half the size of that displayed in round 1 (based on the principal component

measure). The newly-introduced “Tariff Hurts Prices” narrative induces a similar response: when information that tariffs have hurt U.S. consumers is conveyed, participants also shift towards voicing more support for limits on imports (Column 6). These patterns hold too when we use alternative methods to combine the responses across the individual questions (i)-(v), such as an unweighted average or a factor analysis approach (see Appendix Table 3).²⁶ Given its persistence and robustness, this finding – that narratives on the beneficial price effects of trade can instead prompt protectionist reactions – cannot be easily put aside as an isolated result.

We make further use of the validation questions in rounds 2-4 to confirm that, at least at a self-reported level, the treatment effects we have identified are linked to participants’ engagement with the received information. Relative to the control group, respondents who were exposed to a treatment were more likely to “somewhat agree” or “strongly agree” with the statement that the information received had affected their views on trade policy (Column 7, ordered logit regression).²⁷ Also, when asked (post-treatment) to assess the impact that being open to trade has had for most Americans, each of the treatment groups was *less* likely to register “extremely good” or “somewhat good” as a response (Column 8, ordered logit). This is notable that even respondents who received information about the possible benefits of openness to trade – to either service-sector jobs or goods prices – became more likely to express a negative view on how trade has impacted most Americans. These findings also provide reassurance against the possibility that participants might be shading their answers towards what they perceive to be the survey’s objective: The narratives on the beneficial dimensions of trade actually induce a pro-protectionist response and a worsening view of trade, contrary to the anticipated direction of experimenter demand effects.²⁸

In sum, the 2020-2022 rounds show that the manner in which these information treatments move trade policy preferences has been stable over time despite the ongoing disruptions from the Covid-19 pandemic and the U.S.-China trade war.²⁹ Information on manufacturing job losses from trade intensifies preferences for import restrictions, while alternative information on potential gains from trade likewise raises protectionist sentiment. These shifts are accompanied by a stronger belief that trade has had a bad impact on most Americans. Whereas various studies have found that short cues or primes about the positive effects of trade yield a zero effect on trade policy preferences (Hiscox 2006, Rodriguez et al. 2021, Stantcheva 2022, Coppock 2023), the evidence-based information we administered on the benefits of trade goes further in that it induces a pro-protectionist backfire effect.

26. Appendix Table 3 also confirms that the findings are robust when pooling all four rounds of data.

27. Each of the dependent variables in Columns 7 and 8 of Table 4 is a categorical variable with five bins. We run an ordered probit regression with the same right-hand side variables as equation (1), and report the marginal effect on the predicted probability that either the fourth or fifth highest bin is selected as the response.

28. We should also note that no monetary stakes were conditioned on specific responses being given. More broadly, see De Quidt et al. (2018) who present evidence that experimenter demand effects are relatively small.

29. The round 2 survey overlapped with the early months of the Covid-19 pandemic and events related to the Black Lives Matter movement. In Appendix Table 6, we control for a county-by-week measure of individual mobility constructed by Safegraph from cell phone signal data as a proxy for the severity of local Covid-19 lockdowns. We also control for the occurrence of county-level Black Lives Matter protests by week, drawn from the Armed Conflict Location & Event Data (ACLED) project. Including these variables does not affect the information treatment effects in the Table 4, Column 6 specification.

Respondent characteristics. Before moving on to further results on the information treatments, we briefly discuss the role of several respondent characteristics. Appendix Table 2 reports the full set of coefficients from Columns 6-8 of Table 4, where the dependent variables are, respectively, the first principal component measure of preferences for import limits and the responses to the two validation questions on the role of the received information.

Consistent with previous research (e.g., Blonigen 2011), older participants are more likely to support protection. The effect of gender on trade policy preferences is imprecisely estimated (Column 2, Appendix Table 2), although women are more likely to have a negative view of the impact of trade on most Americans (Column 4, c.f., Scheve and Slaughter 2001, Mayda and Rodrik 2005, Blonigen 2011). The role of education is similarly mixed: those with some college education express a more positive view of the impact of trade, but this is not reflected in their choices over trade policies. Controlling for education, household income is positively correlated with support for protection, as is being employed in agriculture, mining, or manufacturing (relative to being employed in services).³⁰

Of note, political affiliation plays an important role in explaining where members of the U.S. public are positioned in their trade policy views. In contrast to previous decades, Republican supporters are more likely to favor import restrictions during our sample period than independents, with the opposite being true for Democrat supporters, a reflection of how decisively the Trump administration moved the Republican party away from support of free trade. It is worth pointing out, too, that Republicans are more intense in their support for protection (coefficient: 0.625) than Democrats are in their opposition to it (-0.141), relative to independents.³¹

5.3 Additional Information Treatments

We turn now to discuss several variants of the narratives that were incorporated in rounds 2-4. These explore mixed information treatments and whether the baseline findings might be attributable to certain key wording.

Mixed Information Treatments. In Panel A of Table 5, we examine the effects when the “Trade Hurts Jobs” and “Trade Helps Jobs” narratives are jointly presented, in both possible orders. To provide points of comparison for the sizes of the effects, the sample in this panel comprises the control group together with the “Trade Hurts Jobs”, “Trade Helps Jobs”, and the two mixed treatment groups.³² We find that exposure on the same screen to both jobs-related narratives weakly dampens protectionist responses relative to receiving only the information that “Trade Hurts Jobs”. This dampening is more pronounced if the “Trade Helps Jobs” narrative is sequenced after “Trade Hurts Jobs”; however, the treatment effect is not lowered to the point where it becomes equivalent to only receiving the “Trade Helps Jobs” content. This suggests that even while positive narratives about the effect of trade on jobs cannot fully dissuade respondents from favoring limits on imports, these can still modestly counteract the strength of information

30. Interestingly, participants who took the survey on a mobile device are also more in favor of protection.

31. Related to this, viewership of Fox News is associated with a stronger preference for protection.

32. We verify in Appendix Table 4 that the results hold when we pool all the baseline and variant treatments – regardless of whether these are jobs- or prices-related – in the same regression.

that focuses exclusively on the job losses associated with trade.³³

“Sans Cheaper” Treatment. With the “Trade Helps Prices” narrative, one concern is that participants might be associating the word “cheaper” with “lower quality”. If read in this way, the narrative would be seen as conveying a drawback of imports, which could explain the shift in favor of import restrictions. We therefore ran a “sans Cheaper” version of the “Trade Helps Prices” treatment, in which the phrase “availability of cheaper goods” was replaced with “increased availability of goods” (see Appendix A.1 for the full wording). In Panel B of Table 5, we find that this modified wording continues to induce preferences in favor of protection, with a treatment effect comparable in size to that of the original “Trade Helps Prices” and “Tariff Hurts Prices” narratives.³⁴ The potential negative connotations of the adjective “cheaper” are thus unlikely to be driving this backfire effect.

“Sans China” Treatments. Our baseline narratives are written around the rise in imports following China’s accession to the WTO, and so it could be that the mere mention of “China” is evoking the protectionist reaction. We therefore explore whether removing “China” from the narrative – by referring instead to an “increase in imports from the rest of world” (see Appendix A.1) – has any bearing on trade policy preferences; we implemented such “sans China” versions for the “Trade Hurts Jobs”, “Trade Helps Jobs”, and “Trade Helps Prices” treatments.³⁵

Panel C of Table 5 illustrates with the “Trade Helps Prices” treatment that the protectionist turn in preferences is not dampened by dropping “China” from the wording.³⁶ Put otherwise, there is a tendency among the U.S. public to opt for more limits on imports even when China is not explicitly named. Furthermore, in Appendix Table 12, we show that the treatment effect associated with each of the three “sans China” narratives is statistically indistinguishable from that of its respective counterpart “with China” narrative; for example, when directly comparing the “Trade Hurts Jobs” and “Trade Hurts Jobs sans China” treatments relative to the control group, the “sans China” narrative also induces protectionist responses and we cannot reject a null of equal-sized treatment coefficients. We will have more to say by way of interpreting this finding in Section 6.3.³⁷

33. Respondents who received the mixed job treatments also became more negative in their views on the impact of trade on most Americans (Column 8, Appendix Table 4), but expressed a lower degree of confidence in their assessment on this front (Column 9). Being informed of both the positive and negative effects of trade may thus lower one’s certainty about the net impact, which could explain the milder protectionist response.

34. The sample in Panel B of Table 5 comprises the control group, as well as the “Trade Helps Prices”, “Tariff Hurts Prices”, and “Trade Helps Prices sans Cheaper” treatment groups from rounds 2-4. This “sans Cheaper” treatment effect is robust when instead pooling across all baseline and variant treatment groups (see Appendix Table 4).

35. We did not run a “sans China” version of the “Tariff Hurts Prices” treatment, given the difficulty of disassociating the recent U.S. tariffs from the main foreign country that they were levied on.

36. The sample in Panel C of Table 5 comprises the control group, as well as the “Trade Helps Prices”, “Tariff Hurts Prices”, and “Trade Helps Prices sans China” treatment groups from rounds 2-4.

37. Di Tella and Rodrik (2020) find that when they manipulate the identity of the foreign country to which jobs are lost from a developed country (France) to a developing country (Cambodia), this significantly raises preferences for protection. We did not experiment with a change in country name in our treatments due to budget constraints. Moreover, as we will see in Table 8, our survey participants cited concerns about trade with China even when randomized to a “sans China” treatment, which underscores the difficulty of dampening the salience of China as a trade partner in the minds of the U.S. general public.

Table 5: Other Information Treatments
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Trade Policy Qns	(1)	(2)	(3)
	First prin. component	Did info affect views?	Impact of trade on Americans
	OLS	Ord. logit	Ord. logit
Panel A: Mixed Job Treatments			
Trade Hurts Jobs	0.237*** [0.043]	0.047*** [0.015]	-0.249*** [0.016]
Trade Helps Jobs	0.074* [0.045]	0.030* [0.016]	-0.022 [0.015]
Trade Hurts Helps Jobs	0.177*** [0.048]	0.035** [0.016]	-0.093*** [0.016]
Trade Helps Hurts Jobs	0.206*** [0.045]	0.043*** [0.016]	-0.208*** [0.017]
Observations	8,561	8,561	8,561
(Pseudo) R-squared	0.158	0.0467	0.0584
Panel B: “Sans Cheaper” Price Treatment			
Trade Helps Prices	0.111*** [0.042]	0.025 [0.015]	-0.061*** [0.016]
Tariff Hurts Prices	0.103** [0.042]	0.045*** [0.016]	-0.168*** [0.016]
Trade Helps Prices sans Cheaper	0.167*** [0.049]	0.015 [0.017]	-0.059*** [0.017]
Observations	7,147	7,147	7,147
(Pseudo) R-squared	0.151	0.0518	0.0533
Panel C: “Sans China” Price Treatment			
Trade Helps Prices	0.115*** [0.042]	0.027* [0.015]	-0.062*** [0.016]
Tariff Hurts Prices	0.107** [0.043]	0.046*** [0.016]	-0.171*** [0.016]
Trade Helps Prices sans China	0.134*** [0.049]	0.004 [0.017]	-0.056*** [0.017]
Observations	7,153	7,153	7,153
(Pseudo) R-squared	0.143	0.0492	0.0515
Individual, County, Week, Rand. order Controls?	Y	Y	Y

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the “Control” group who received no information treatment (the omitted category), as well as those who received the treatments listed in the respective panels. The dependent variable in Column 1 is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade; that in Column 2 is a categorical variable for degree of agreement with the statement that the information received affected one’s views on trade policy (1=“Strongly disagree”, 5=“Strongly agree”); while that in Column 3 is a categorical variable asked post-treatment on views on the impact that trade has had for most Americans (1=“Extremely bad”, 5=“Extremely good”). The controls included (but not reported) are as listed in the Table 3 footnotes, as well as Democrat and Republican dummies for the candidate supported in the last presidential election; Column 1 further includes the randomization order in which “More Limits on Imports” appeared in the “Most Preferred” list of 8 policies. Column 1 reports an OLS regression. Columns 2-3 report marginal effects from ordered logit regressions, on the predicted probability that either the fourth or fifth highest ordered category is selected as the response; all marginal effects are evaluated setting the initial values of the treatment dummies to zero, while setting all other right-hand side controls at their in-sample mean values. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5%, and 10% levels respectively.

5.4 Comprehension and Attention

We investigate two other possible explanations for the protectionist responses to the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments; these relate to how well the respondents understood or engaged with the narratives.

Comprehension. Could the backfire effect be due to a basic misreading of the topic of the narrative? For example, even if a participant received the “Trade Helps Prices” narrative, the mention of the word “trade” might evoke an association with “jobs” because of the (arguably) more widespread coverage of news on the impact of trade on jobs in the U.S. media.

Table 6 addresses this possibility. We revert here to the set of four baseline treatments from Table 4; we use the specification in (1), but with responses to the end-of-survey recall question (from rounds 2-4) as the dependent variable.³⁸ Reassuringly, we find that respondents were, on average, able to recall the subject matter of the narrative they received: Those assigned to the “Trade Helps Prices” and “Tariff Hurts Prices” treatments were significantly less likely to say that the information was on the topic of trade and jobs (Column 1, logit regression), and more likely to indicate that it was on the relationship between trade and prices (Column 2). Likewise, those in the “Trade Hurts Jobs” or the “Trade Helps Jobs” treatment groups were, on average, able to correctly identify that the content was on the topic of jobs rather than prices. In Columns 3-4, we re-run our regression based on the principal component measure of trade policy preferences, respectively, for the subsamples with incorrect versus correct recall of the information. This reveals that the tilt toward protectionist preferences in reaction to information about the positive impacts of trade is *not* driven exclusively by participants who mistook the broad subject matter of the narrative. We in fact obtain a stronger, statistically significant backfire effect – in particular, to information about how trade could boost service-sector jobs – among respondents who correctly identified the topic of the treatment they read.³⁹

Attention. While participants may have been able to distinguish between jobs- and prices-related content, the degree to which they absorbed the information could still vary with the level of attention paid. Table 7 examines the potential role of attention, where we proxy for this using the time spent on the treatment screen. We confirm that individuals who took more time – specifically, an above-median duration for a given treatment – are more likely to correctly answer the recall question on the topic of the narrative they received (Column 1, logit regression).⁴⁰ Exploring further, we find that the expressed trade policy preferences (summarized by

38. Appendix Table 5 presents summary statistics for the end-of-survey information recall question. We control in all columns of Table 6 for the full set of covariates from the Table 4, Column 6 specification.

39. From Appendix Table 5, the share of the control group who selected “I did not receive any information” was low at around 20%, which suggests that this recall question could have been too subtle and thus less informative about the recall abilities of those in the control group. We therefore take an agnostic stance by including the entire control group in both Columns 3 and 4, for the “Recall Incorrect” and “Recall Correct” regression samples, respectively. Our results are similar if we split up the control group across the Columns 3 and 4 samples according to whether “I did not receive any information” was the recall question response (available on request).

40. Throughout Table 7, we take the median or quintile cutoffs separately for each treatment group within each survey round. In Column 1, we omit participants who did not receive any treatment, since we cannot compute a meaningful treatment duration for this group. For the same reason, we pool all respondents in the Control group into the omitted category in Columns 2-4 of this table.

Table 6: End-of-Survey Recollection of Treatment Information
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Dependent variable	(1)	(2)	(3)	(4)
	Info received on jobs? Logit	Info received on prices? Logit	First prin. component OLS	First prin. component OLS
			Recall incorrect	Recall correct
Trade Hurts Jobs	0.130*** [0.018]	-0.044*** [0.017]	0.133*** [0.048]	0.391*** [0.058]
Trade Helps Jobs	0.149*** [0.016]	-0.062*** [0.017]	0.028 [0.052]	0.140** [0.056]
Trade Helps Prices	-0.050*** [0.015]	0.139*** [0.018]	0.116** [0.058]	0.105** [0.051]
Tariff Hurts Prices	-0.056*** [0.015]	0.125*** [0.016]	0.100* [0.055]	0.103** [0.049]
Individual, County, Week, Rand. order Controls?	Y	Y	Y	Y
Observations	9,275	9,275	5,569	5,945
(Pseudo) R-squared	0.0422	0.0313	0.147	0.165

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the “Control” group who received no information treatment (the omitted category), as well as those who received the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments. The dependent variable in Columns 1 is a dummy variable for whether the respondent indicated the information received was on the relationship between trade and jobs; that in Column 2 is a dummy variable for whether the respondent indicated the information received was on the relationship between trade and prices; while that in Columns 3-4 is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade. The controls included (but not reported) are as listed in the Table 3 footnotes, as well as Democrat and Republican dummies for the candidate supported in the most recent presidential election. In Columns 1 and 2, the randomization order variable is the order in which “about jobs” (respectively, “about prices”) appeared in the answer options to the respondent; in Columns 3-4, the randomization variable is the order in which “More Limits on Imports” appeared in the “Most Preferred” list of 8 policies. Columns 1-2 report marginal effects from logit regressions, evaluated setting the initial values of the treatment dummies to zero, while setting all other right-hand side controls at their in-sample mean values. Columns 3-4 report OLS regressions. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5%, and 10% levels respectively.

the principal component measure) differ systematically based on attention paid. The protectionist reaction to information is evident among those who spent less time on the treatments (Column 2, below-median duration). On the other hand, as we successively limit the sample to those who spent more time on the treatment screen – respectively, above-median (Column 3) and top-quintile (Column 4) duration – the treatment coefficients in response to the “Trade Helps Jobs”, “Trade Helps Prices”, or “Tariff Hurts Prices” information decrease in magnitude and wane in statistical significance. Respondents with a longer treatment duration thus appear to have better comprehended and reacted less adversely to the various narratives on the benefits of trade, although not to the extent that the treatment effect reverses signs. At the same time, they expressed stronger support for protection in reaction to the “Trade Hurts Jobs” information compared to those who paid less attention.⁴¹

41. In Appendix Table 7, we show that this result – that those who spent a longer duration on the treatment screen tend to update their trade policy preferences in line with the information – holds even within each of the subsamples of respondents with incorrect (respectively, correct) recall of the subject of the treatment.

Table 7: Role of Attention Paid as Captured by Treatment Duration
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Trade Policy Qns	(1)	(2)	(3)	(4)
	Info correct?	First prin. component	First prin. component	First prin. component
	Logit	OLS	OLS	OLS
Treatment duration:	All	Below median	Above median	Top quintile
Above-med. treatment duration	0.167*** [0.016]			
Above-med. survey duration	-0.005 [0.014]			
Trade Hurts Jobs		0.162*** [0.050]	0.330*** [0.057]	0.497*** [0.080]
Trade Helps Jobs		0.116** [0.050]	0.051 [0.057]	0.057 [0.087]
Trade Helps Prices		0.141*** [0.050]	0.090* [0.053]	0.060 [0.076]
Tariff Hurts Prices		0.154*** [0.048]	0.057 [0.058]	0.020 [0.082]
Individual, County, Week, Rand. order Controls?	Y	Y	Y	Y
Observations	7,036	5,760	5,754	3,643
(Pseudo) R-squared	0.043	0.143	0.172	0.158

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the “Control” group who received no information treatment (the omitted category), as well as those who received the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments. The dependent variable in Column 1 is a dummy variable equal to one if the respondent correctly identified the nature of the information received in the survey (“about jobs”, “about prices”, “none”), while that in Columns 2-4 is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade. Columns 2-4 samples comprise all “Control” observations and respondents who spent respectively a below median, above median, and top quintile duration on their received information treatment (computed within treatment-by-round). The controls included (but not reported) are as listed in the Table 3 footnotes, as well as Democrat and Republican dummies for the candidate supported in the last presidential election; Columns 2-4 further include the randomization order in which “More Limits on Imports” appeared in the “Most Preferred” list of 8 policies. Column 1 reports marginal effects from logit regressions, evaluated by setting the initial values of all right-hand side controls at their in-sample mean values. Columns 2-4 report OLS regressions. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5%, and 10% levels respectively.

Together, these patterns are consistent with greater attention inducing trade policy preferences that are in closer alignment with the direction of the information. This suggests that time-intensive information treatments that hold individuals’ attention for a longer duration may be more effective in communicating the potential benefits of trade to the U.S. general public, to the extent that one can elicit this longer attention span successfully.

6 Exploring the Mechanisms

We have just presented evidence showing that the backfire effect cannot easily be attributed to unintended interpretations of specific wording or to a misunderstanding of the narrative topic. Moreover, we have seen in Table 4 that respondents who received a treatment were uniformly

more likely to indicate that the information affected their views on trade policy (Column 7), shifting them toward a more negative assessment of the impact of trade on Americans (Column 8). This motivates us to develop a model of belief updating in the formation of trade policy preferences to help rationalize these findings. The model will provide guidance on further empirical specifications, to explore how information received might interact with prior beliefs – such as those rooted in one’s political identity – in shaping policy preferences.

6.1 A Model of Belief Updating and Trade Policy Preferences

We consider a setting where individuals evaluate their preferences over two possible policies: free trade (*FT*) and limits on trade (*LT*). Whether or not an individual ultimately prefers *FT* or *LT* depends on their perceptions and beliefs over whether free trade is “good” or “bad”. To be more formal, let A denote the “state” that “free trade is good”, on which an individual places prior probability $p(A)$; this prior can differ across individuals, but we omit indexing it explicitly to avoid extra notation. On the other hand, A^c refers to the “state” that “trade is bad”, which holds with complementary prior probability $1 - p(A)$.

In this stylized setting, the evidence-based information acts as a signal S that prompts individuals to update their priors. To allow for a rich pattern of responses in trade policy preferences, we consider a generalized belief updating process adapted from Charness and Dave (2017) and Benjamin (2019) that accommodates departures from Bayes rule. Conditional on receiving a treatment narrative S , we specify the posterior odds that “trade is bad” (i.e., of the state A^c relative to A) to be:

$$\frac{1 - \pi(A|S)}{\pi(A|S)} = \left(\frac{p(S|A^c)}{p(S|A)} \right)^{\kappa_S} \frac{1 - p(A)}{p(A)}. \quad (2)$$

We adopt the natural assumption that $\frac{p(S|A^c)}{p(S|A)} < 1$ for signals S that highlight a positive aspect of openness to trade; in words, the individual perceives that there is a higher probability of receiving information about jobs- or price-related gains from trade under A (“trade is good”) than under A^c (“trade is bad”). Conversely, we assume that $\frac{p(S|A^c)}{p(S|A)} > 1$ if the signal S is about a negative consequence of trade (e.g., job losses).

Observe that $\kappa_S = 1$ corresponds to conventional Bayesian updating. More broadly, we will consider a specification for κ_S that allows the response to S to vary with the nature of the signal received and its interaction with one’s prior beliefs. Following Benjamin (2019), we let: $\kappa_S = c_{0,S} + c_{1,S} \mathbf{1}(S \text{ confirms } A^c) + c_{2,S} \mathbf{1}(S \text{ disconfirms } A^c)$, where $c_{0,S} + c_{1,S} > 0$ and $c_{0,S} + c_{2,S} < 0$; this captures a situation of “prior-biased updating”, where both confirming and disconfirming signals induce the individual to update their beliefs in favor of their priors.

To be more specific, S is said to “confirm” A^c if:

$$\frac{p(S|A^c)}{p(S|A)}, \frac{1 - p(A)}{p(A)} > 1 \text{ or } \frac{p(S|A^c)}{p(S|A)}, \frac{1 - p(A)}{p(A)} < 1.$$

For example, if S is the information that “Trade Hurts Jobs” (so $\frac{p(S|A^c)}{p(S|A)} > 1$), and the individual has a prior belief that places a greater probability on free trade being bad (i.e., $\frac{1-p(A)}{p(A)} > 1$),

the formulation in (2) implies that this prior is reinforced in their posterior beliefs: $\frac{1-\pi(A|S)}{\pi(A|S)} > \frac{1-p(A)}{p(A)} > 1$, since $c_{0,S} + c_{1,S} > 0$. On the other hand, S is “disconfirming” of A^c if either:

$$\frac{p(S|A^c)}{p(S|A)} > 1 > \frac{1-p(A)}{p(A)} \text{ or } \frac{1-p(A)}{p(A)} > 1 > \frac{p(S|A^c)}{p(S|A)}.$$

To see how this plays out, suppose as before that the individual has a prior belief that tilts toward “trade is bad”, but they instead receive information that “Trade Helps Jobs” (for which $\frac{p(S|A^c)}{p(S|A)} < 1$). With (2), the individual does not simply discard the signal; rather, since $\kappa_S = c_{0,S} + c_{2,S} < 0$ and thus $\left(\frac{p(S|A^c)}{p(S|A)}\right)^{\kappa_S} > 1$, they update in a manner that doubles down on their prior once again, so that $\frac{1-\pi(A|S)}{\pi(A|S)} > \frac{1-p(A)}{p(A)} > 1$.

In Section A.4 in the appendix, we embed this belief updating process in a discrete choice model of preferences over the two policies, FT and LT . The individual’s utility under each policy features a systematic component (which is a weighted average over their utility conditional respectively on A and A^c), plus an idiosyncratic component (an iid Gumbel shock term). The individual then expresses a preference for LT over FT if the former is the policy state that maximizes expected utility, when this is evaluated using posterior probabilities as given by (2).

We show in the appendix that this delivers an empirical specification of the form:

$$\mathbf{1}(\text{Policy}_i) = \sum_{b=1}^B \alpha_b \mathbf{1}(\text{Treatment}_i = b) \times x_i + \sum_{b=1}^B \beta_b \mathbf{1}(\text{Treatment}_i = b) + \gamma X_i + \epsilon_i, \quad (3)$$

where x_i is a respondent characteristic (whose main effect is included in the vector X_i of controls). The above augments (1) with interaction terms between the treatment dummies and x_i , with the latter being a variable that correlates with the baseline beliefs (i.e., priors) that respondent i holds on the desirability of free trade. Intuitively, the coefficient α_b speaks to whether trade policy preferences are updated in line with Bayes rule (uniformly in the direction of the signal regardless of one’s priors), or whether there are differential treatment effects that reveal how prior beliefs might mediate one’s reaction to the conveyed information. More concretely, suppose that x_i correlates positively with respondents’ prior inclination toward protectionism (such as an indicator variable for Republican supporters). Finding that $\alpha_b > 0$ across all treatments would then suggest that high- x_i respondents are updating their beliefs on the desirability of trade in a manner that is prior-biased, given that their preferences for protection are amplified regardless of whether the information conveyed is on the gains or losses from trade.

6.2 Heterogeneous Responses to Information Treatments

We consider a broad set of observables x_i that have been identified in the trade policy literature as potential markers of one’s predisposition toward protectionism. Based on the review of this body of work in Section 2, we group the x_i ’s under four headings for different motivations for these preferences: (a) economic self-interest; (b) sociotropic concerns; (c) behavioral factors; and (d) political identity. While this provides a convenient way to organize our findings, we recognize that

some traits may not fall neatly under a single heading: for example, an individual’s education level could affect both their personal economic situation and their concern with the societal impact of openness to trade (c.f., Hainmueller and Hiscox 2006).

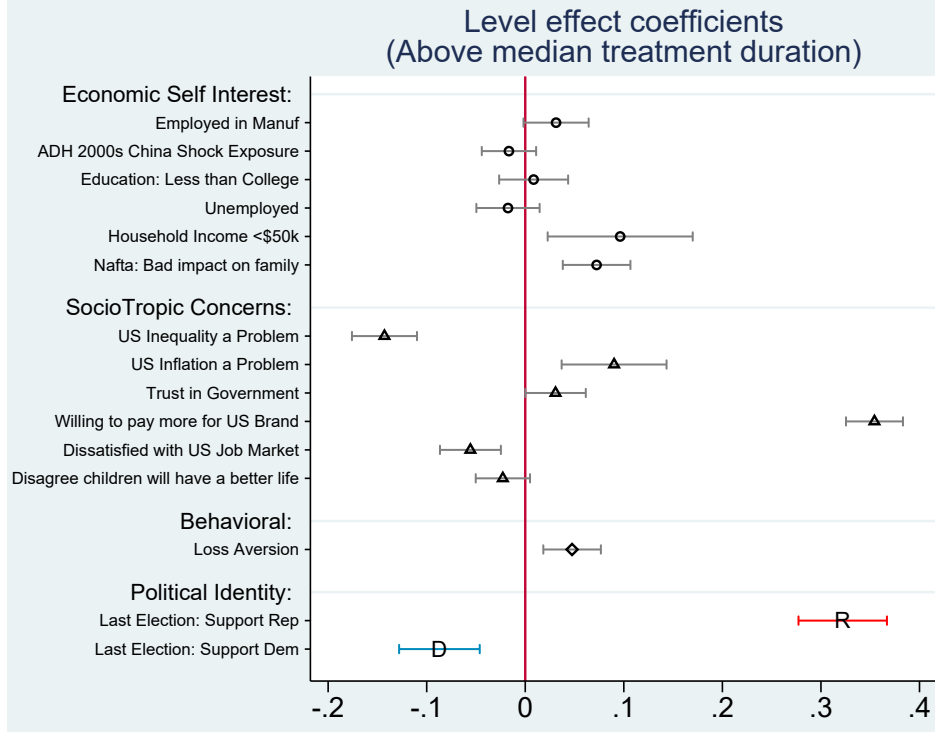
In what follows, we report OLS regressions of (1) and (3) that use the principal component measure of protectionist preferences as the dependent variable. Figure 1 illustrates the level effect coefficients of the respondent characteristics; each coefficient is from a separate regression based on (1), but run without the treatment dummies, while adding x_i as necessary to the right-hand side (if it is not already included in X_i). Figure 2 then presents the interaction coefficients (the α_b ’s); we run separate regressions of (3) for each x_i , that include the four baseline treatment dummies – “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, “Tariff Hurts Prices” – and their interactions with the respondent characteristic in question.⁴² (We z-score each x_i to facilitate comparison of the coefficient magnitudes.) Figures 1 and 2 are based on a sample that comprises the rounds 2-4 respondents in the control group, together with those in the treatment groups who spent an above-median duration on the treatment screen; these are in principle higher-quality observations from participants who paid more attention to and were better able to recall the information content (based on our discussion of Table 7). We obtain qualitatively similar but at times less precisely estimated patterns when using all participants who received these baseline narratives, consistent with this interpretation that the responses from those who spent a longer duration on the treatment screen are less noisy (Appendix Figures 1-2).

To preview what we find, we uncover a number of respondent characteristics that interact with the information in a meaningful way. This includes several economic variables (e.g., household income, personal exposure to NAFTA) and non-economic forces (e.g., outlook for future generations, loss aversion). Across these characteristics, a common theme emerges: for individuals who might be seen as more pre-disposed toward protectionism, exposure to information at odds with these priors induces a doubling-down in trade policy preferences. This is especially notable for the political identity variables: Republican and Democrat supporters move in opposite directions in the intensity of their protectionist preferences following the information treatments, with each side’s updating in their beliefs on trade being biased toward their respective party-line priors, instead of toward the actual content of the information.

Economic self-interest. We consider the potential role of personal exposure to import competition through one’s industry of employment, geographic location, or skill level. These are captured respectively by: whether the respondent is a manufacturing sector worker, the Autor et al. (2013) measure of local labor market exposure to imports from China, and whether the respondent has less than college-level education. Manufacturing workers are marginally more inclined to support protectionist policies (Figure 1), but the interactions of each of these three variables with the treatment dummies otherwise yield indistinct results (Figure 2). While one might have hypothesized that exposure to adverse trade shocks could make individuals’ preferences for protection more responsive to the “Trade Hurts Jobs” treatment or less responsive to

42. To be clear, each panel in Figure 2 illustrates the interaction coefficients for a given treatment b , across the separate regressions for the different x_i ’s; the underlying regressions are reported in tabular form in Appendix Tables 8-10. We do not run the interactions jointly with all the x_i ’s given sample size constraints.

Figure 1: Respondent Characteristics and Preferences for Protection
(Level Effects)



Notes: Coefficient point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Each coefficient is from a separate OLS regression; sample comprises respondents in the “Control” group, and respondents in the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups who spent an above-median duration on the treatment screen, from Round 2 (2020), Round 3 (2021), and Round 4 (2022). Each respondent characteristic is expressed as a z-score.

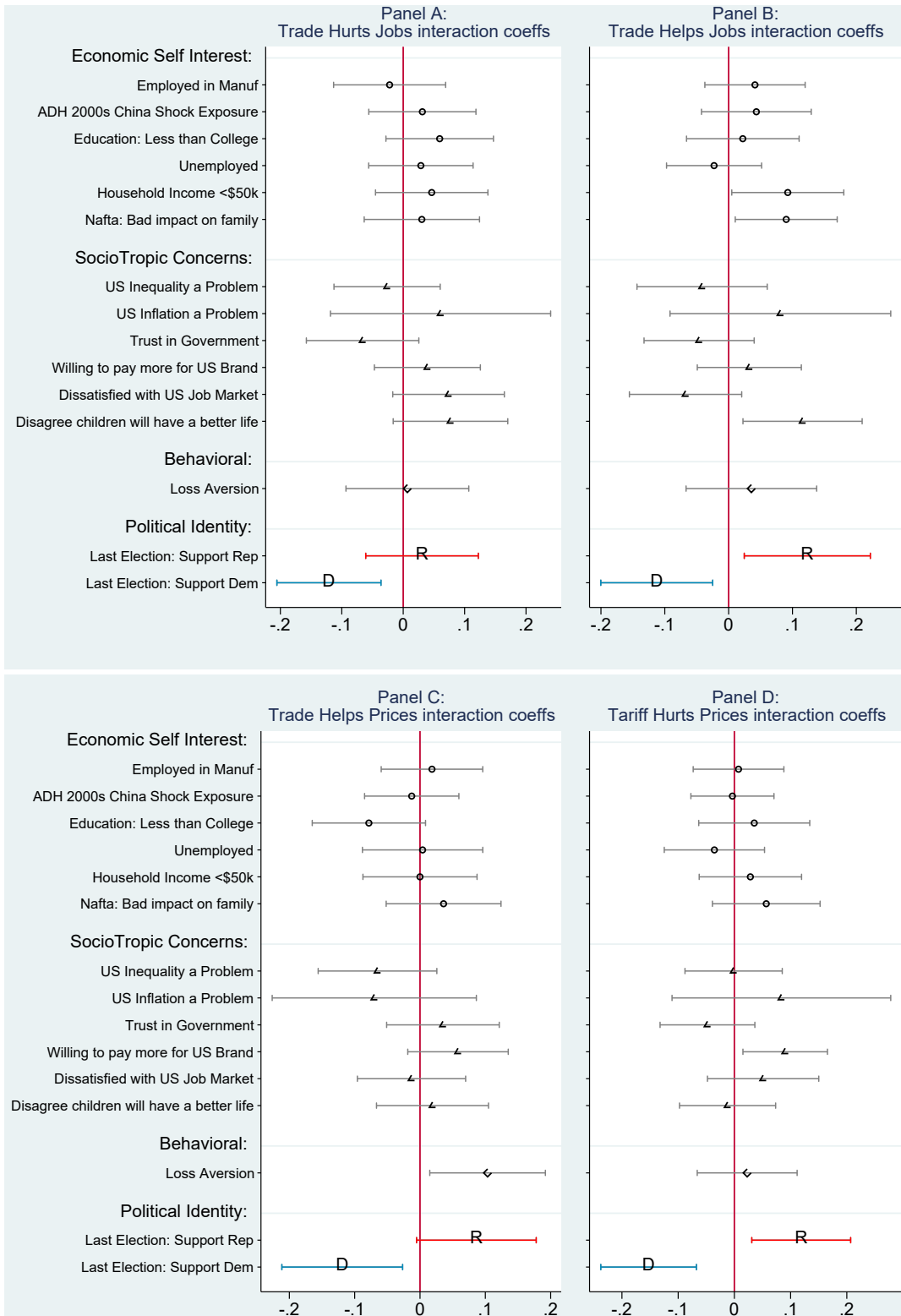
evidence on the benefits of trade, we do not find such patterns in practice.⁴³

We also examine several more direct measures of respondents’ economic situation, namely: whether they are unemployed, whether they are from a low-income household (<\$50,000 annual income), and their assessment of the impact NAFTA has had on “you and your family”. Respondents from lower-income backgrounds and those who perceive a negative impact from NAFTA tend to favor more limits on trade (Figure 1), and this preference intensifies when they are presented with information that trade can have positive job impacts (Figure 2, Panel B). One interpretation here is that evidence-based information that conflicts with respondents’ priors on trade – that stem in particular from these features of their economic situation – can, in fact, amplify protectionist sentiment.

Sociotropic concerns. Trade policy preferences can also be shaped by concerns over the impact of trade on society as a whole (Mansfield and Mutz 2009). We explore a range of variables, elicited prior to the treatment component of the survey, that speak to such broader motivations. We consider respondents’ views on: whether inequality in the U.S. is a problem, whether inflation in the U.S. is a problem, their degree of trust in the government, whether they are willing to pay

43. See, however, Ardanaz et al. (2013), who find that economic self-interest variables play a mediating role in shaping views toward trade in a survey-based experiment run in Argentina with short frames as treatments.

Figure 2: Respondent Characteristics and Preferences for Protection
(Interaction Effects, above-median treatment duration sample)



Notes: Coefficient point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Each coefficient is from a separate OLS regression with treatment group indicators interacted with the respondent characteristic in question; sample comprises respondents in the “Control” group, and respondents in the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups who spent an above-median duration on the treatment screen, from Round 2 (2020), Round 3 (2021), and Round 4 (2022). Each respondent characteristic is expressed as a z-score.

more for a U.S. brand, their satisfaction with the state of the U.S. job market, and their outlook on whether future generations will have a better life. Looking briefly at level effects, respondents who express a willingness to pay more for U.S.-branded goods are more inclined to limit trade, as are those who view inflation as a problem (Figure 1).⁴⁴

Turning to the interaction effects, we do not find sharp patterns of heterogeneous responses to the treatments, with two exceptions: among those who are more pessimistic about the outlook for future generations and are provided information that “Trade Helps Jobs” (Figure 2, Panel B), and among those who are willing to pay more for a U.S. brand and are shown the “Tariff Hurts Prices” narrative (Panel D). These cases are interesting, as the information on the benefits of trade (or the losses from enacting trade barriers) appears to trigger stronger protectionist preferences in the treated individuals, whom one might expect to already lean in favor of trade restrictions.

Loss aversion. To examine this behavioral trait, we draw on studies such as Kahneman et al. (1991) to elicit preferences over receiving a discount versus avoiding a surcharge of an equal monetary amount (as described earlier in Section 3). Individuals who are more loss averse express stronger support for limits on imports (Figure 1), in line with the hypothesis in Freund and Ozden (2008) and Tovar (2009) that loss aversion would lead to a downweighting of the potential benefits from being open to trade. More loss-averse individuals also react to the “Trade Helps Prices” treatment by doubling down on this preference for protection (Figure 2, Panel C). This repeats the pattern seen above, where information dissonant with one’s predisposition toward protection can end up reinforcing those preferences.

Political identity. We call attention to the role of political identity, given how party affiliation has increasingly shaped individuals’ preferences in the U.S. over a range of policies, including policies pertaining to trade (Grossman and Helpman 2021). As mentioned earlier, Republican supporters are more strongly in favor of protection during our sample period, with Democrats less inclined toward such restrictions than Republicans and independents. This is illustrated in the coefficient plot in Figure 1, which moreover confirms that political identity is among the most quantitatively important correlates of protectionist preferences across the respondent characteristics we examine.

The manner in which political identity interacts with the information treatments is especially striking. Efforts to convey either the jobs- or price-related benefits of trade instead accentuate calls for protection among Republican supporters (Figure 2, Panels B-D); meanwhile, the “Trade Hurts Jobs” narrative that conforms more with their political identity also mildly reinforces these preferences for limits on trade (Panel A, although this effect is not statistically significant). On the other end of the political spectrum, respondents who supported the Democratic party’s presidential candidate see their preferences for protection dampened after being presented with information that “Trade Hurts Jobs” (Panel A) or with information that openness to trade has

44. Interestingly, those who see inequality as a problem are less in favor of trade protection (Figure 1); what we find is that they instead tend to rank alternatives such as more progressive taxes and a higher minimum wage among their top-three “Most Preferred” policies (available on request). Similarly, those who are dissatisfied with the health of the U.S. job market are significantly more likely to pick “more progressive taxes” and a “higher minimum wage” as a top-three preferred policy rather than “more limits on imports”.

beneficial effects either for jobs or for prices (Panels B-D). This differential response along party lines is not easily explained by mechanisms in conventional trade theories. One could posit, for instance, that individuals who read the “Trade Helps Prices” narrative could have correctly reasoned that there must be domestic industries hurt by import competition, prompting them to then favor more protectionism. That said, it is unclear why this line of reasoning would necessarily resonate more strongly with Republicans than Democrats, without circling back to the observation that the two parties differ in their relative positioning on trade policy.

The pattern of responses described above is instead consistent with prior-biased updating, as discussed in Section 6.1. For Republican supporters, narratives such as “Trade Hurts Jobs” that are align with their political priors succeed in reinforcing their preferences for protection. However, narratives on the benefits of trade (or the harm caused by tariffs) are unable to move their views in the direction of the information: on the contrary, Republicans react to the disconfirming information by coming down more strongly in favor of limiting trade. We see an analogous pattern with Democrats, who appear to update toward the trade policy position of the party they identify with (i.e., being less opposed to trade restrictions) regardless of the content of the narrative.⁴⁵ This finding that information can reinforce prior beliefs stemming from one’s political identity echoes results uncovered in other contexts, such as Mullainathan and Shleifer (2005) and Chopra et al. (2022) who study the demand for news sources. It also connects with a strand of work on the efficacy of fact-checking, which has demonstrated that such efforts can fail to persuade and can even lead individuals to dig in their heels toward views rooted in one’s partisanship (Nyhan and Reifler 2010, Nyhan et al. 2020, Barrera et al. 2020).⁴⁶

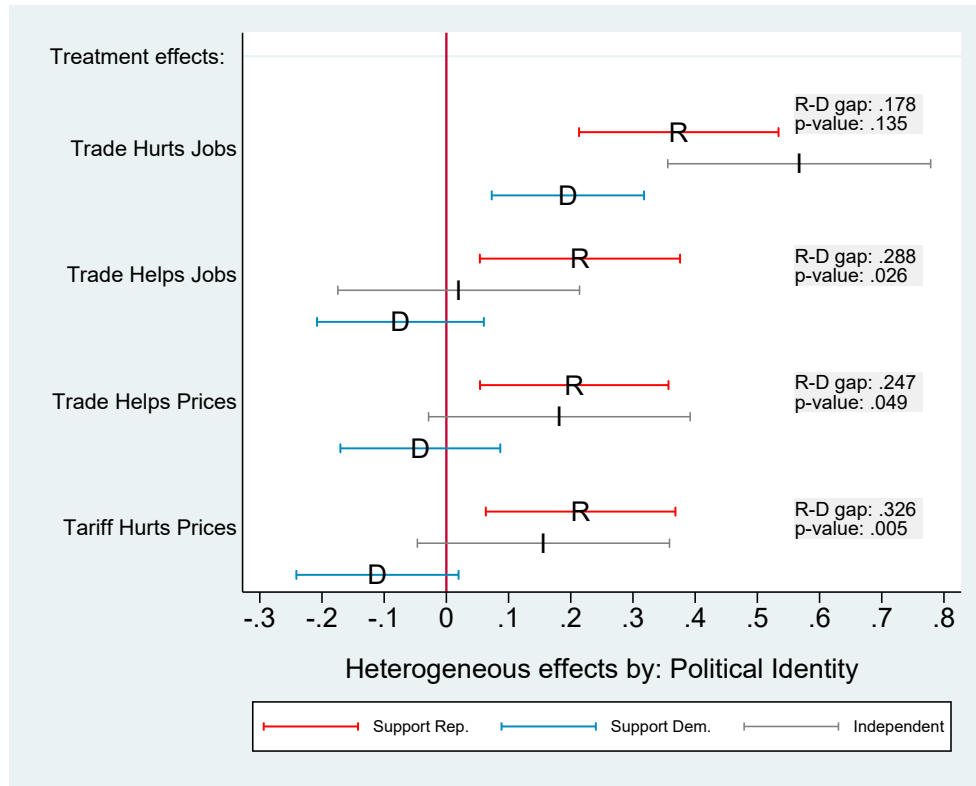
We highlight two consequences of this prior-biased updating. First, it results in a further polarization of Republican and Democrat supporters on the issue of trade. Figure 3 displays this divergence in trade policy preferences. For this illustration, we have re-run the specification in (3) while jointly including indicator variables for Republicans, Democrats, and independents as the characteristics (x_i ’s) whose interaction effects are considered; as these three categories span all observations, we drop the main effects of the treatment dummies, and de facto estimate treatment effects for each of these three subgroups in response to each narrative. The “R-D gap” reported is the difference in treatment effects across party identity lines and thus speaks to how much further Republicans’ and Democrats’ protectionist preferences have moved apart. We can reject a null hypothesis of no divergence (i.e., equal treatment effects for Republicans and Democrats) for the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments (p-values < 0.05). The extent of this polarization is also sizeable: the gap between Republicans and Democrats in the intensity of their support for protection widens by a further one-third (between 20.9%-38.2% across the four treatments) of the initial difference.⁴⁷

45. A related interpretation noted in the behavioral economics literature is information avoidance (Goldman et al. 2017). However, our findings that participants responded significantly to the treatments (relative to the control group), and that they could on average successfully recall the broad content of the narrative they read, suggests that participants did not simply avoid or disregard the information.

46. An overview of work in political science on this topic is provided by Nyhan (2021). In the context of trade policy, Porter and Wood (2022) find that fact-checking treatments intended to correct misperceptions about openness can induce more favorable attitudes toward free trade, but these effects are weaker for Republicans.

47. For example, consider the “Trade Helps Jobs” treatment. The initial difference between the Republican and

Figure 3: Heterogeneous Treatment Effects and Prior-Biased Updating by Political Identity



Notes: Coefficient point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Based on an OLS regression with treatment group indicators interacted with a full set of political identity dummies for “Support Rep.,” “Support Dem.,” and “Independents”; sample comprises respondents in the “Control” group, and respondents in the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups who spent an above-median duration on the treatment screen, from Round 2 (2020), Round 3 (2021), and Round 4 (2022). For each treatment group, the “R-D gap” reports the difference between the treatment effect point estimates for “Support Rep.” and “Support Dem.”; the p-value reported is for a test with null hypothesis that the “R-D gap” equals zero, based on the full covariance matrix of the estimated regression coefficients.

Second, the doubling down on the part of Republicans in response to information about the gains from trade (or the losses from tariffs) is crucial for explaining why we see a backfire effect for these treatments in our overall sample. As Figure 3 shows, the effects of the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” narratives on Democrat supporters are, in fact, mildly negative, although this is statistically indistinguishable from zero (as it is too in the case of independents). In other words, the backfire effect would not be detected but for Republicans’ protectionist response to this set of information treatments.

Taking stock, we have uncovered several dimensions of heterogeneity in the survey responses that are relevant for understanding our main finding of a backfire effect. Drawing on the insights of the model from Section 6.1, respondents do not appear to update their preferences over trade policy uniformly in the direction of the information as one might expect under Bayes rule; instead, the treatments amplify the prior beliefs of key groups within the U.S. general population regardless of the content of the information conveyed (prior-biased updating). Of particular note

Democrat dummy coefficients when regressing (1) for this sample of interest is 0.854. The widens by a further 0.288 upon exposure to the “Trade Helps Jobs” treatment, or $0.288/0.854 \approx 33.7\%$ of the initial gap.

is the role of party political identity: The backfire effect in reaction to evidence on the gains from trade can be accounted for by a doubling down in protectionist preferences among those who, because of their political identity, are already skeptical toward free trade.

6.3 Why Limit Imports? Jobs and China

To gain more insight into the specific beliefs and concerns that account for preferences for protection, we directly asked participants who chose “more limits on imports” as a “Most Preferred” policy their reasons behind this choice. (Recall that starting in round 3, participants were directed to these follow-up questions – described in Appendix A.2 – if they selected this from the list of eight policies.) Note that the reasons identified by those in the control group should in principle reflect a set of underlying prior concerns that are motivating protectionist preferences among the U.S. general public, since this group was not exposed to any of the information treatments. On the other hand, for those who received a narrative on the potential benefits of trade (or the costs from imposing trade barriers), their responses on these follow-up questions helps shed light on why these information treatments “backfired”.

Table 8 reports summary statistics on respondents’ degree of agreement with each of the reasons we proposed for favoring “more limits on imports” (from 1 for “strongly disagree” to 5 for “strongly agree”).⁴⁸ Several key messages emerge. While one hypothesis is that respondents in the treatment groups might have found the evidence unpersuasive, or might distrust the findings of academic “experts” (e.g., Cheng and Hsiaw 2022), this does not appear to be the main explanation behind their support for protection against imports. In fact, participants who received the “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatments tended to assign a lack of persuasion among the lowest, if not the lowest, agreement scores as a reason for their choosing “more limits on imports” as a “Most Preferred” policy.

It is instead concerns over how “imports often compete for jobs with U.S. workers” and about “imports from countries such as China” that saw the highest agreement scores, consistently across all control and treatment groups. Of note, there is a similarly high degree of agreement registered on concerns for U.S. jobs, regardless of whether the respondent read a narrative about jobs (e.g., “Trade Hurts Jobs”, “Trade Helps Jobs”) or about prices (e.g., “Trade Helps Prices”, “Tariff Hurts Prices”). Likewise, concern about trade with China is uniformly cited as a leading reason for preferring “more limits on imports”, even for the versions of the narratives that omit any mention of “China” while providing otherwise identical information (e.g., comparing “Trade Helps Jobs” with “Trade Helps Jobs sans China”, or “Trade Helps Prices” with “Trade Helps Prices sans China”). For the “sans China” treatment groups, the information thus appears to evoke prior perceptions not only of trade in general but also of trade specifically with China.⁴⁹

48. The reasons were once again presented in random order on the survey screen, to avoid systematic biases if for example there was a tendency to agree more strongly with reasons that appeared at the top of the list.

49. This rise in U.S. protectionist sentiment in response to the emergence of an economic challenger is not without precedent. In the late 1980s, there was a surge in calls for barriers to trade and investment directed against Japan. For example, a *New York Times* poll conducted at that time found that Americans viewed the economic power of Japan as a greater threat to U.S. national security than the military power of the Soviet Union, and about one in four supported restricting Japanese imports “a great deal” (*New York Times* 1990).

Table 8: Reasons for More Limits on Imports as a Most Preferred Policy
Summary Statistics (Pooled: Round 3, 2021; Round 4, 2022)

Reasons: 5=Strongly agree 1=Strongly disagree	Not persuaded	Lower quality	National security	Compete with US jobs	Concern abt imports from China	Other more important concerns
Information Treatment:						
Control (N = 302)	—	3.54 [1.08]	3.41 [1.12]	3.85 [1.09]	3.96 [1.08]	3.61 [1.01]
Trade Hurts Jobs (N = 270)	3.84 [1.02] ^{Pers.}	3.74 [0.96]	3.47 [1.00]	4.09 [0.91]	4.04 [0.99]	3.81 [0.94]
... sans China (N = 183)	3.65 [1.07] ^{Pers.}	3.64 [1.01]	3.56 [1.05]	3.98 [1.01]	3.83 [1.11]	3.70 [1.02]
Trade Helps Jobs (N = 238)	3.62 [1.04]	3.79 [1.04]	3.69 [1.07]	4.06 [0.98]	4.29 [0.97]	3.80 [0.95]
... sans China (N = 171)	3.63 [0.92]	3.63 [1.00]	3.40 [0.99]	3.92 [0.96]	3.94 [1.18]	3.60 [0.99]
Trade Helps Prices (N = 250)	3.30 [1.02]	3.75 [0.99]	3.43 [1.06]	4.06 [0.99]	4.05 [0.98]	3.90 [0.85]
... sans China (N = 256)	3.50 [1.08]	3.70 [1.09]	3.53 [1.13]	4.09 [1.00]	4.08 [1.08]	3.81 [1.03]
Tariff Hurts Prices (N = 245)	3.27 [1.06]	3.61 [1.15]	3.50 [1.11]	3.94 [1.05]	4.12 [1.01]	3.70 [0.99]
Other treatments (N = 775)	3.49 [1.09]	3.72 [1.06]	3.55 [1.05]	4.01 [1.00]	4.09 [0.99]	3.68 [0.95]

Notes: Mean values reported, with standard deviations in brackets. Based on the sample of Round 3 (2021) and Round 4 (2022) respondents who selected “More Limits on Import” as a top three “Most Preferred” policy and were directed to these follow-up questions on their reasons for this preference. For the “Trade Hurts Jobs” and “Trade Hurts Jobs sans China” treatments, the summary statistics in the first column (with superscript “Pers.”) are agreement scores with being “persuaded that imports have hurt jobs in the U.S.”, rather than being “not persuaded”. The “Other treatments” row pools the agreement scores across the “Trade Hurts Helps Jobs”, “Trade Helps Hurts Jobs”, and “Trade Helps Prices sans Cheaper” treatment groups.

Observe too that despite not receiving any narrative, the control group returned agreement scores with each of the listed reasons that are very similar to those expressed by the information treatment groups (except for “not persuaded”, which was omitted for the control group). In particular, concerns about U.S. jobs and about trade with China resonated most (once again) with the control group as reasons for favoring protection, which indicates that these worries and reservations are rooted in prior beliefs.

We show in Appendix Table 11 that the above conclusions based on simple averages hold too when we examine the detailed variation at the individual level. We consider OLS regressions of the form:

$$Agreement_{ir} = \alpha Order_{ir} + \sum_{l=1}^5 \beta_l \mathbf{1}(Reason_r = l) + \delta_i D_i + \epsilon_{ir}, \quad (4)$$

where the dependent variable is the agreement (on a scale of 1 to 5) expressed by individual i on reason r for preferring “more limits on imports”; the $\mathbf{1}(Reason_r = l)$ ’s are a set of indicator variables for the listed reasons, and $Order_{ir}$ is the randomization order in which reason r appeared on i ’s survey screen. With respondent fixed effects D_i included, (4) exploits within-individual variation over the proposed reasons for favoring import restrictions. The results in Appendix Table 11 confirm that concerns about American jobs and about trade with China received stronger agreement from respondents than the other listed reasons (“not persuaded/persuaded”, “quality”, “national security”, “other reasons”); this is true both when pooling all observations (Column 1), as well as within each control or treatment group (Columns 2-10).

The themes of “jobs” and “China” stand out visually too as prior concerns when we perform

a word-cloud analysis of text responses (Figure 4). When participants were allowed to freely express any other reasons they had for favoring “more limits on imports” as a “Most Preferred” policy, phrases that appeared with high frequency included: “American Jobs”, “Made in the USA”, “America First”, “Self Reliance”, and “China” (Panel A). This is true both for groups exposed to a treatment about jobs (left) and for groups exposed to a treatment about prices (right).⁵⁰ Similarly, when asked to identify countries on which they favored placing more limits on imports, the most common response written was “China”, followed by “Russia” (Panel B). This is true regardless of whether the participant was shown a narrative that mentioned China (left) or a narrative “sans China” (right).⁵¹ We corroborate these patterns more formally in a series of logit regressions (Appendix Table 12): There is no statistically significant difference in the propensity to identify China as a target country for more limits on imports across the control group, and the groups who received the “with” and “sans China” versions of the same information treatment. Likewise, there is no meaningful difference in the occurrence of “jobs” in the open-text responses across the control, and the “jobs” or “price” treatment groups. Note that the prominence of “China” as a prior concern across treatment groups can also rationalize why we find no significant difference in the size of the treatment effects across the “with” versus “sans China” versions of each narrative, in the degree to which each shifts preferences in favor of trade protection (see Appendix Table 13).⁵²

As a final exercise, we build on the discussion in Section 6.2 to show how political identity is highly relevant for explaining the intensity of these prior beliefs and concerns about free trade. For this, we augment the specification in (4) as follows:

$$\begin{aligned}
 Agreement_{ir} = & \alpha Order_{ir} + \sum_{l=1}^5 \gamma_{l,R} \mathbf{1}(Reason_r = l) \times Rep_i + \sum_{l=1}^5 \gamma_{l,D} \mathbf{1}(Reason_r = l) \times Dem_i \\
 & + \delta_i D_i + \delta_{tr} D_{tr} + \epsilon_{ir},
 \end{aligned} \tag{5}$$

where Rep_i (respectively, Dem_i) is an indicator for whether i self-identified as a Republican (respectively, Democratic) supporter in the most recent U.S. presidential election. Equation (5) is a stringent specification: the D_i 's sweep up the role of both observable and unobserved respondent characteristics (including the main effects of Rep_i and Dem_i), while the D_{tr} 's are fixed effects which control for the average degree of agreement expressed by each treatment group t

50. Specifically, the word cloud on the left of Figure 4, Panel A pools responses across the “Trade Hurts Jobs”, “Trade Hurts Jobs sans China”, “Trade Helps Jobs”, and “Trade Helps Jobs sans China” treatment groups, while that on the right pools across the “Trade Helps Prices” and “Trade Helps Prices sans China” treatments.

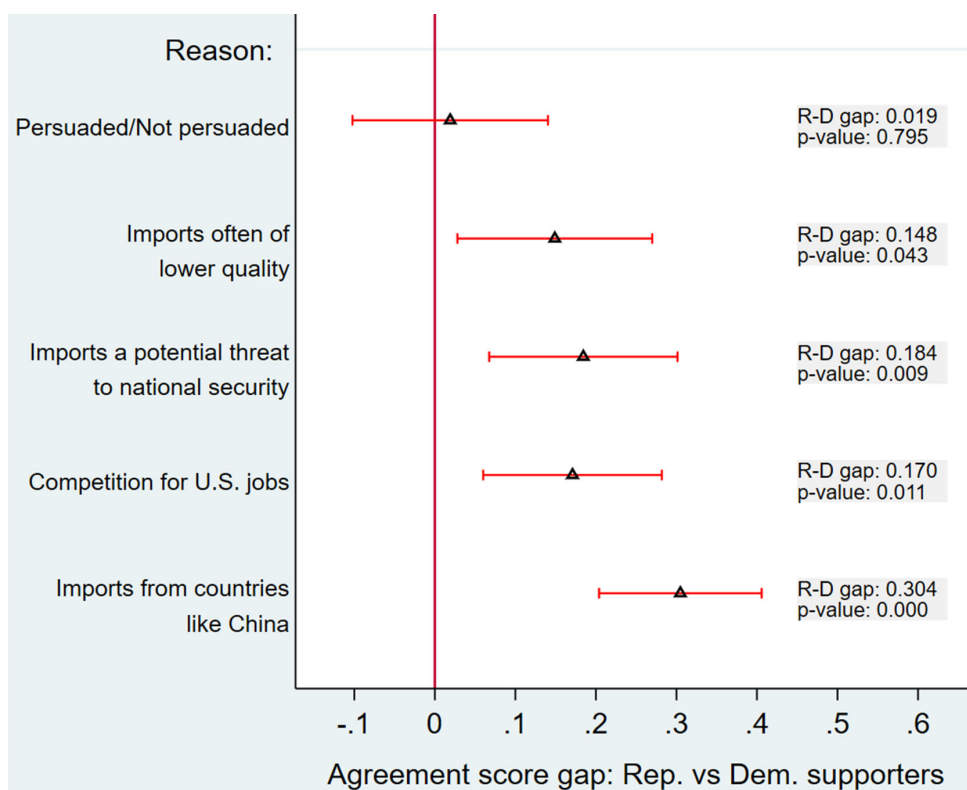
51. The word cloud on the left of Figure 4, Panel B pools responses from the “Trade Hurts Jobs”, “Trade Helps Jobs”, and “Trade Helps Prices” treatment groups, while that on the right pools across the three corresponding “sans China” treatments. For completeness, Appendix Figure 3 presents word clouds comparing the frequency of “China” (as a response to the “which countries” question) across the “jobs” versus “prices” treatment groups and likewise comparing the occurrence of “jobs” (as a response to the “other reasons” question) across the “with” versus “sans China” treatment groups. The focal nature of “China” and “jobs” is evident across all groups, even in this alternative comparison.

52. In Appendix Table 14, we show that the agreement scores with concerns about jobs and about trade with China did not differ in a significant way across respondents who received the “with China” and “sans China” versions of each treatment, barring one exception. (The “Trade Helps Prices” treatment group recorded stronger concerns about trade with China than the “Trade Helps Prices sans China” treatment group.)

with each reason r .

Figure 5 summarizes the difference between the Republican and Democrat coefficients, $\gamma_{l,R} - \gamma_{l,D}$, that we estimate from (5) for each of the reasons l . We find that Republicans are significantly more intense compared to Democrats in their agreement with concerns about the quality of imports, about national security, about competition for American jobs, and especially about trading with China, as grounds for backing more limits on imports (p-values < 0.05). The intensity of these beliefs and concerns – particularly over China as a trade partner country – thus appears to be shaped (at least in part) by political identity, and this, in turn, motivates these respondents to express a preference for more protection. This underscores a key challenge in communicating information on the benefits of trade to the U.S. general public: Given the tendency we have seen in Section 6.2 for individuals to double down on their priors based on their political identity, such information is unlikely to succeed, particularly with Republican supporters, unless it also seeks to address strongly-held concerns about U.S.-China trade relations, and even (by extension) about the countries’ broader geopolitical competition.

Figure 5: Why “More Limits on Imports”? The Role of Political Identity (Interaction Effects)



Notes: Point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Based on OLS regressions on the Round 3 (2021) and Round 4 (2022) samples; comprising respondents in the “Control” group, and the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups. The dependent variable in each column is the agreement score (on a scale of 1-5) with a given reason for selecting “More limits on imports” as a top-three Most Preferred policy. All regressions include individual fixed effects, a full set of treatment-group-by-reason dummies, as well as reason dummies interacted with “Support Rep.” and “Support Dem.”. Point estimates reported for each stated reason are the difference between the “Support Rep.” and “Support Dem.” interaction coefficients; the p-value is from a test with null hypothesis that the “R-D gap” equals zero, based on the full covariance matrix of the estimated regression coefficients.

7 Concluding Discussion

Can evidence-based information shift preferences towards trade policy? To address this question, we have administered a series of surveys over 2018-2022 that contain randomized information treatments, each with concise summaries of evidence established by economic researchers on the gains and losses from trade.

We find that the answer to our motivating question is: “Yes”, but in complex and unanticipated ways. On the one hand, information that trade has had adverse impacts on manufacturing jobs (“Trade Hurts Jobs”) raises support for restrictions against imports. On the other hand, we uncover novel evidence of a backfire effect, wherein narratives that point to job gains in non-manufacturing sectors (“Trade Helps Jobs”) or to gains through lower consumer prices (“Trade Helps Prices”, “Tariff Hurts Prices”) also induce an intensification in preferences for protection. The reactions to information presented in this format on the gains versus losses from trade are thus highly asymmetric.

We document patterns of heterogeneous responses that shed light on underlying mechanisms. The information treatments interact in a significant way with several markers of individuals’ priors on trade, most notably with their political identity as a Republican or Democratic party supporter: When the received information is dissonant with the trade policy positions of the party they identify with, it instead reinforces their preferences in favor of their priors (rather than in favor of the conveyed information). This is consistent with a pattern of prior-biased belief updating that we flesh out in a simple model, and it results in a greater polarization of the two parties’ supporters in their preferences over trade policy. In response to narratives on the gains from trade, this doubling-down in Republicans’ support for protectionism is sufficiently strong to account for the backfire effect observed in our overall sample. Last but not least, respondents who ranked “more limits on imports” highly as a preferred policy consistently cited concerns about competition for jobs and over trade with China as leading reasons for their policy choice. That these rationales were volunteered by those who received a narrative that did not explicitly mention “jobs” or “China” – and even by those in the control group – points to the prior prevalence of these concerns among the U.S. general public.

Our findings give pause to whether short evidence-based messaging can help to steer public views over trade policy, much as economists might place stock in this as a mode for communicating information about the gains from trade. If policy preferences can be shifted by such narratives in unintended directions, this should prompt some rethinking on the role of information in the political economy of trade policy formation. We highlight two pertinent challenges on this front. First, our findings in Section 6.3 call for more to be done to focus public messaging and education on assuaging the two key sets of prior concerns – over the potential impact on American jobs, as well as over trade with China – to pre-empt the backfire effect against evidence presented on the benefits of openness to trade. On concerns over American jobs, we would hypothesize that one may be able to make inroads on this front through efforts, such as in Stantcheva (2022), to improve understanding of the scope for redistributive policies aimed at remediating the adverse effects of trade. Information that engages respondents for a longer duration may also hold promise (e.g., see our results on “attention” in Table 7), subject to the caveat that one would

first need to be able to elicit this participation in more time-intensive treatments. On the other hand, we are more pessimistic about the ability of economics-based evidence to move the U.S. general public on their concerns about U.S.-China trade, as these may well extend beyond the purview of economics to considerations related to geopolitical competition and rivalry.

Second, recent trends in the policy position, particularly of the Democratic party, are likely to further complicate the task of public communication on trade policy. As clear already from our survey responses, Republicans are more intense in their support for protection than Democrats are in their opposition to it (relative to independents). Under the Biden administration, the Democratic party has arguably become more lukewarm on free trade, as seen from the continued use of the Trump-era tariffs, calls to encourage friendshoring and nearshoring, as well as the roll-out of industrial policies to bolster domestic manufacturing (Alfaro and Chor 2023). If anything then, concerns about American jobs and about the geoeconomic risk of China as a trade partner are poised to intensify among Democratic party supporters. This expands the challenge of communicating to the U.S. general public that there are tradeoffs and pitfalls when protectionist policies are pursued.

References

- Acemoglu, Daron and Pascual Restrepo, (2017), “Robots and Jobs: Evidence from US Labor Markets,” NBER Working Paper 23285.
- Adão, Rodrigo, Arnaud Costinot, Dave Donaldson, and John A. Sturm, (2023), “Why Trade is Not Free? A Revealed Preference Approach,” NBER Working Paper 31798.
- Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso, (2018), “Intergenerational Mobility and Preferences for Redistribution,” *American Economic Review* 108(2): 521-554.
- Alesina, Alberto, Armando Miano, and Stefanie Stantcheva, (2023), “Immigration and Redistribution,” *Review of Economic Studies* 90(1): 1-39.
- Alfaro, Laura, and Davin Chor, (2023), “Global Supply Chain: The Looming “Great Reallocation”,” NBER Working Paper 31661, for the proceedings of the Jackson Hole Symposium.
- Amiti, Mary, Mi Dai, Robert C. Feenstra, and John Romalis, (2017), “How Did China’s WTO Entry Benefit U.S. Consumers?” NBER Working Paper 23487.
- Amiti, Mary, Stephen J. Redding, and David E. Weinstein, (2019), “The Impact of the 2018 Tariffs on Prices and Welfare,” *Journal of Economic Perspectives* 33(4): 187-210.
- Ardanaz, Martin, M. Victoria Murillo, and Pablo M. Pinto, (2013), “Sensitivity to Issue Framing on Trade Policy Preferences: Evidence from a Survey Experiment,” *International Organization* 67: 411-437.
- Autor, David, David Dorn, and Gordon Hanson, (2013), “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review* 103(6): 2121-2168.
- Autor, David, David Dorn, and Gordon Hanson, (2016), “The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade,” *Annual Review of Economics* 8: 205-240.
- Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi, (2020), “Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure,” *American Economic Review* 110(10): 3139–3183.
- Bai, Liang, and Sebastian Stumpner, (2019), “Estimating US Consumer Gains from Chinese Imports,” *American Economic Review: Insights* 1(2): 209-224.
- Baldwin, Robert E., (1989), “The Political Economy of Trade Policy,” *Journal of Economic Perspectives* 3(4): 119-135.

- Balistreri, Edward J., (1987), "The Performance of the Heckscher-Ohlin-Vanek Model in Predicting Endogenous Policy Forces at the Individual Level," *Canadian Journal of Economics* 30(1): 1-17.
- Barrera, Oscar, Sergei Guriev, Emeric Henry, and Ekaterina Zhuravskaya, (2020), "Facts, Alternative Facts, and Fact-Checking in Times of Post-Truth Politics," *Journal of Public Economics* 182: 1-19.
- Beaulieu, Eugene, (2002a), "Factor or Industry Cleavages in Trade Policy? An Empirical Analysis of the Stolper-Samuelson Theorem," *Economics and Politics* 14: 99-131.
- Beaulieu, Eugene, (2002b), "The Stolper-Samuelson Theorem Faces Congress," *Review of International Economics* 10: 343-360.
- Benjamin, Daniel, (2019), "Errors in Probabilistic Reasoning and Judgment Biases," in *Handbook of Behavioral Economics: Applications and Foundations* 1, edited by B. Douglas Bernheim, Stefano DellaVigna, David Laibson, Volume 2, 69-186.
- Blanchard, Emily, Chad Bown and Davin Chor, (2022), "Did Trump's Trade War Impact the 2018 Election?" NBER Working Paper 26434.
- Blanga-Gubbay, Michael, Paola Conconi, and Mathieu Parenti, (2022), "Lobbying for Globalization," CEPR Discussion Paper 14597.
- Blonigen, Bruce A., (2011), "Revisiting the Evidence on Trade Policy Preferences," *Journal of International Economics* 85: 129-135.
- Blonigen, Bruce A., and Jacob McGrew, (2014), "Task Routineness and Trade Policy Preferences," *Economics and Politics* 26: 505-518.
- Bombardini, Matilde, (2008), "Firm Heterogeneity and Lobby Participation," *Journal of International Economics* 75: 329-348.
- Bonomi, Giampaolo, Nicola Gennaioli, and Guido Tabellini, (2021), "Identity, Beliefs, and Political Conflict," *Quarterly Journal of Economics* 136(4): 2371-3411.
- Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro, (2019), "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica* 87: 741-835.
- Charness, Gary, and Dave, Chetan, (2017), "Confirmation Bias with Motivated Beliefs," *Games and Economic Behavior* 104: 1-23.
- Che, Yi, Yi Lu, Justin Pierce, Peter Schott, and Zhigang Tao, (2022), "Did Trade Liberalization with China Influence U.S. Elections?" *Journal of International Economics* 139, 103652.
- Cheng, Ing-Haw, and Alice Hsiaw, (2022), "Distrust in Experts and the Origins of Disagreement," *Journal of Economic Theory* 200, 105401.
- Choi, Jiwan, Ilyana Kuziemko, Ebonya L. Washington, and Gavin Wright, (2021), "Economic and Political Effects of Trade Deals: Evidence from NAFTA," NBER Working Paper 29525.
- Chopra, Felix, Ingar Haaland, and Christopher Roth, (2022), "The Demand for News: Accuracy Concerns versus Belief Confirmation Motives," mimeo.
- Chow, Rosalind M., and Galak, Jeff, (2012), "The Effect of Inequality Frames on Support for Redistributive Tax Policies," *Psychological Science* 23(12): 1467-1469.
- Colantone, Italo, Gianmarco Ottaviano, and Piero Stanig, (2022), "The Backlash of Globalization," in Elhanan Helpman, Gita Gopinath and Kenneth Rogoff, eds., *Handbook of International Economics*, Vol.5: 405-477, North-Holland, Amsterdam (Netherlands).
- Colantone, Italo, and Piero Stanig, (2018), "Global Competition and Brexit," *American Political Science Review* 112(2): 201-218.
- Conconi, Paola, Giovanni Facchini, and Maurizio Zanardi, (2014), "Policymakers' Horizon and Trade Reforms: The Protectionist Effect of Elections," *Journal of International Economics* 94(1): 102-118.
- Coppock, Alexander, (2023), *Persuasion in Parallel: How Information Changes Minds about Politics*, University of Chicago Press.
- Couper, Mick P., Christopher Antoun, and Aigul Mavletova, (2017), "Mobile Web Surveys: A Total Survey Error Perspective," in *Total Survey Error in Practice*, eds. Paul P. Biemer et al., John Wiley and Sons, Chapter 7, 133-154.

- DellaVigna, Stefano, Woojin Kim, and Elizabeth Linos, (2023), “Bottlenecks for Evidence Adoption,” *Journal of Political Economy*, forthcoming.
- De Quidt, Jonathan, Johannes Haushofer, and Christopher Roth, (2018), “Measuring and Bounding Experimenter Demand,” *American Economic Review* 108(11): 3266-3302.
- Dippel, Christian, Robert Gold, Stephan Heblich, and Rodrigo Pinto, (2022), “The Effect of Trade on Workers and Voters,” *Economic Journal* 132(641): 199-217.
- Di Tella, Rafael, and Dani Rodrik, (2020), “Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys,” *Economic Journal* 130: 1008-1030.
- Facchini, Giovanni, and Anna Maria Mayda, (2008), “From Individual Attitudes Towards Migrants to Migration Policy Outcomes: Theory and Evidence,” *Economic Policy* 56: 651-713.
- Facchini, Giovanni, and Anna Maria Mayda, (2009), “Does the Welfare State Affect Individual Attitudes Toward Immigrants? Evidence Across Countries,” *The Review of Economics and Statistics* 91: 295-314.
- Facchini, Giovanni, Yotam Margalit, and Hiroyuki Nakata, (2022), “Countering Public Opposition to Immigration: The Impact of Information Campaigns,” *European Economic Review* 141: 103959.
- Fernandez, Raquel, and Dani Rodrik, (1991), “Resistance to Reform: Status Quo Bias in the Presence of Individual-Specific Uncertainty,” *American Economic Review* 81(5): 1146-1155.
- Fetzer, Thiemo, and Carlo Schwarz, (2021), “Tariffs and Politics: Evidence from Trump’s Trade wars,” *Economic Journal* 131(636): 1717-1741.
- Fisman, Raymond, Keith Gladstone, Ilyana Kuziemko, and Suresh Naidu, (2020), “Do Americans Want to Tax Wealth? Evidence from Online Surveys,” *Journal of Public Economics* 188: 104207.
- Freund, Caroline, and Caglar Ozden, (2008), “Trade Policy and Loss Aversion,” *American Economic Review* 98(4): 1675-1691.
- Gennaioli, Nicola, and Guido Tabellini, (2023), “Identity Politics,” CEPR Discussion Paper 18055.
- Gentzkow, Matthew, and Jesse M. Shapiro, (2010), “What Drives Media Slant? Evidence from U.S. Daily Newspapers,” *Econometrica* 78 (1): 35-71.
- Gentzkow, Matthew, and Jesse M. Shapiro, (2011), “Ideological Segregation Online and Offline,” *Quarterly Journal of Economics* 126 (4): 1799-1839.
- Goldman, Russell, David Hagmann, and George Loewenstein, (2017), “Information Avoidance,” *Journal of Economic Literature* 55(1): 96-135.
- Goldberg, Pinelopi, and Tristan Reed, (2023), “Is the Global Economy Deglobalizing? And If So, Why? And What is Next?” prepared for the *Brookings Papers on Economic Activity*.
- Grigorieff, Alexis, Christopher Roth, and Diego Ubfal, (2020), “Does Information Change Attitudes Towards Immigrants? ,” *Demography* 57(3): 1117-1143.
- Grossman, Gene M., and Elhanan Helpman, (1995), “The Politics of Free-Trade Agreements,” *The American Economic Review* 85(4): 667-690.
- Grossman, Gene M., and Elhanan Helpman, (2021), “Identity Politics and Trade Policy,” *The Review of Economic Studies* 88(3): 1101-1126.
- Haaland, Ingar and Christopher Roth, (2020), “Labor Market Concerns and Support for Immigration,” *Journal of Public Economics* 191: 104256.
- Haaland, Ingar, Christopher Roth, and Johannes Wohlfart, (2023), “Designing Information Provision Experiments,” *Journal of Economic Literature* 61(1): 3-40.
- Hainmueller, Jens, and Michael J. Hiscox, (2006), “Learning to Love Globalization: Education and Individual Attitudes Toward International Trade,” *International Organization* 60: 469-498.
- Hiscox, Michael J., (2006), “Through a Glass and Darkly: Attitudes Toward International Trade and the Curious Effects of Issue Framing,” *International Organization* 60: 755-780.

- Hjort, Jonas, Diana Moreira, Gautam Rao, and Juan Francisco Santini, (2021), "How Research Affects Policy: Experimental Evidence from 2,150 Brazilian Municipalities," *American Economic Review* 111(5): 1442-1480.
- Jäkel, Ina C., and Marcel Smolka, (2017), "Trade Policy Preferences and Factor Abundance," *Journal of International Economics* 106: 1-19.
- Kahneman, Daniel, and Amos Tversky, (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica* 47: 263-291.
- Kahneman, Daniel, and Amos Tversky, (1984), "Choices, Values, and Frames," *American Psychologist* 39: 341-350.
- Kahneman, Daniel, Knetsch, Jack, and Thaler and Richard, (1991), "Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias," *Journal of Economic Perspectives* 5(1): 193-206.
- Krishna, Pravin, (1998), "Regionalism and Multilateralism: A Political Economy Approach," *Quarterly Journal of Economics* 113: 227-251.
- Krugman, Paul, (1995), "Growing World Trade: Causes and Consequences," *Brookings Papers on Economic Activity* 26(1): 327-377.
- Krugman, Paul, (2000), "Technology, Trade, and Factor Prices," *Journal of International Economics* 50(1): 51-71.
- Krugman, Paul, (2008), "Trade and Wages, Reconsidered," *Brookings Papers on Economic Activity* 39(1): 103-154.
- Kuziemko, Ilyana, Michael I. Norton, Emmanuel Saez, and Stefanie Stantcheva, (2015), "How Elastic are Preferences for Redistribution? Evidence from Randomized Survey Experiments," *American Economic Review* 105(4): 1478-1508.
- Lake, James, and Jun Nie, (2021), "2020 US Presidential Election and Trump's Trade War." CESifo Working Paper 9669.
- Lawrence, Robert, (2008), *Blue-Collar Blues: Is Trade to Blame for Rising U.S. Income Inequality?* Washington: Peterson Institute for International Economics.
- Lawrence, Robert, and Edwards Lawrence, (2012), "Shattering the Myths About U.S. Trade Policy," *Harvard Business Review*, March.
- Mansfield, Edward D., and Diana C. Mutz, (2009), "Support for Free Trade: Self-Interest, Sociotropic Politics, and Out-Group Anxiety," *International Organization* 63: 425-457.
- Mayda, Anna Maria, (2006), "Who is Against immigration? A Cross-Country Investigation of Individual Attitudes Toward Immigrants," *The Review of Economics and Statistics* 88: 510-530.
- Mayda, Anna Maria, Giovanni Peri and Walter Steingress, (2022), "The Political Impact of Immigration: Evidence from the United States," *American Economic Journal: Applied Economics* 14(1): 358-389.
- Mayda, Anna Maria, and Dani Rodrik, (2005), "Why Are Some People (And Countries) More Protectionist Than Others?" *European Economic Review* 49(6): 1393-1430.
- Méndez, Esteban, and Diana Van Patten, (2022), "Voting on a Trade Agreement: Firm Networks and Attitudes Toward Openness," NBER Working Paper 30058.
- Mullainathan, Sendhil, and Andrei Shleifer, (2005), "The Market for News," *American Economic Review* 95(4): 1031-1053.
- Mutz, Diana, (2021), *Winners and Losers: The Psychology of Foreign Trade*, Princeton University Press.
- New York Times*, (1990), "Americans Voicing Anxiety on Japan As Concern in Tokyo Seems to Soften," 10 July.
- Nguyen, Quynh, (2017), "Mind the Gap?? Rising Income Inequality and Individual Trade Policy Preferences," *European Journal of Political Economy* 50: 92-105.
- Norton, Michael I., and Dan Ariely, (2011), "Building a Better America? One Wealth Quintile at a Time," *Perspectives on Psychological Science* 6(1): 9-12.
- Nyhan, Brendan, and Jason Reifler, (2010), "When Corrections Fail: The Persistence of Political Misperceptions," *Political Behavior* 32: 303-330.

- Nyhan, Brendan, Ethan Porter, Jason Reifler, Thomas J. Wood, (2020), "Taking Fact-Checks Literally But Not Seriously? The Effects of Journalistic Fact-Checking on Factual Beliefs and Candidate Favorability," *Political Behavior* 42: 939-960.
- Nyhan, Brendan, (2021), "Why the Backfire Effect Does Not Explain the Durability of Political Misperceptions," *Proceedings of the National Academy of Sciences* 118(15).
- Ogeda, Pedro Molina, Emanuel Ornelas, and Rodrigo Soares, (2021), "Unions and the Electoral Consequences of Trade Liberalization," CESifo Working Paper Series 9418.
- O'Rourke, Kevin, and Richard Sinnott, (2001), "The Determinants of Individual Trade Policy Preferences: International Survey Evidence," *Brookings Trade Forum*, 157-206.
- Pierce, Justin, and Peter Schott, (2016), "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review* 106(7): 1632-1662.
- Ponzetto, Giacomo, Maria Petrova, and Enikolopov, Ruben, (2020), "The Dracula Effect: Voter Information and Trade Policy," working paper.
- Porter Ethan, and Thomas J. Wood, (2022), "Can Facts Change Minds? The Case of Free Trade," in *The Politics of Truth in Polarized America*, David C. Barker and Elizabeth Suhay, eds., 283-304.
- Rho, Sungmin, and Michael Tomz, (2017), "Why Don't Trade Preferences Reflect Economic Self-Interest?," *International Organization* 71: 85-108.
- Rodríguez Chatruc, Marisol, Ernesto Stein, and Razvan Vlaicu, (2021), "How Issue Framing Shapes Trade Attitudes: Evidence from a Multi-country Survey Experiment," *Journal of International Economics* 129, 103428.
- Rodrik, Dani (1995), "Political Economy of Trade Policy," Gene Grossman and Kenneth Rogoff, eds., *Handbook of International Economics*, Vol.3: 1457-1494, North-Holland, Amsterdam (Netherlands).
- Rotemberg, Julio, (2003), "Commercial Policy with Altruistic Voters," *Journal of Political Economy* 111(1): 174-201.
- Scheve, Kenneth F., and Matthew J. Slaughter, (2001a), "What Determines Individual Trade-Policy Preferences?" *Journal of International Economics* 54: 267-292.
- Scheve, Kenneth F., and Matthew J. Slaughter, (2001b), "Labor Market Competition and Individual Preferences Over Immigration Policy," *The Review of Economics and Statistics* 83: 133-145.
- Soroka, Stuart N., (2006), "Good News and Bad News: Asymmetric Responses to Economic Information," *Journal of Politics* 68: 372-385.
- Stantcheva, Stefanie, (2022), "Understanding of Trade," NBER Working Paper 30040.
- Stantcheva, Stefanie, (2023), "How to Run Surveys: A Guide to Creating your own Identifying Variation and Revealing the Invisible," *Annual Review of Economics*, forthcoming.
- Tovar, Patricia, (2009), "The Effects of Loss Aversion on Trade Policy: Theory and Evidence," *Journal of International Economics* 78(1): 154-167.
- Vivalt, Eva, and Aidan Coville, (2023), "How do Policymakers Update Their Beliefs?" *Journal of Development Economics* 165: 103121.
- Wood, Adrian, (1995), "How Trade Hurt Unskilled Workers," *Journal of Economic Perspectives* 9(3): 57-80.
- Young, Alwyn, (2019), "Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results," *Quarterly Journal of Economics* 134(2): 557-598.

A Online Appendix

A.1 Survey Treatments

The following **preamble** is presented at the start of each of the information treatment narratives (excluding the control group).

How have globalization and imports affected workers and households? Economic researchers have been studying this issue.

“Trade Hurts Jobs” narrative. Based on Autor, Dorn and Hanson (AER 2013), with Figure 1 drawn from their paper:

A line of recent research has shown that the United States substantially increased its imports from China, after China joined the World Trade Organization (WTO) in 2001. This was a major force behind the fall in U.S. employment in the manufacturing sector, as the figure below shows. This led to weak wage growth for the middle- and low-income workers who used to hold these manufacturing jobs.

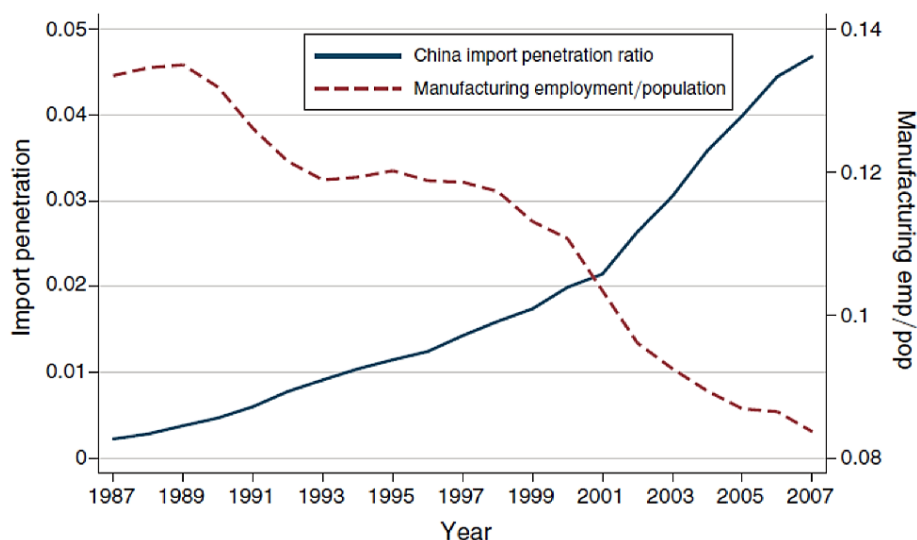
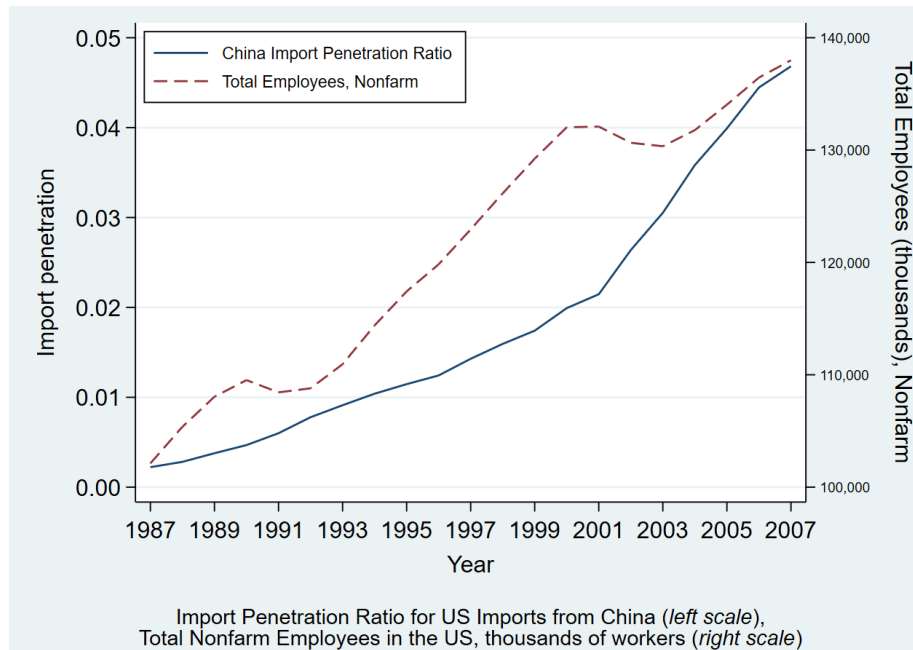


FIGURE 1. IMPORT PENETRATION RATIO FOR US IMPORTS FROM CHINA (left scale), AND SHARE OF US WORKING-AGE POPULATION EMPLOYED IN MANUFACTURING (right scale)

“Trade Helps Jobs”. Based on Caliendo, Dvorkin and Parro (2019):

A line of recent research has shown that the United States substantially increased its imports from China, after China joined the World Trade Organization (WTO) in 2001. This enabled the U.S. to specialize more in the service sectors in which it is particularly productive, helping to increase the number of jobs in the U.S. economy. The figure below shows that the rise in total jobs over the last decades was substantial.



Starting in 2020, two additional treatments were included that mix the “Trade Hurts Jobs” and “Trade Helps Jobs” narratives:

- **“Trade Hurts Helps Jobs”**: “Trade Hurts Jobs” is presented first, followed by “Trade Helps Jobs”. The narratives are prefaced respectively by: “On the one hand, a line of recent research...”, and “On the other hand, another line of recent research...”. (The figures from both narratives were included.)
- **“Trade Helps Hurts Jobs”**: This is analogous to “Trade Hurts Helps Jobs”, except that the order of the “Trade Hurts Jobs” and “Trade Helps Jobs” narratives are reversed.

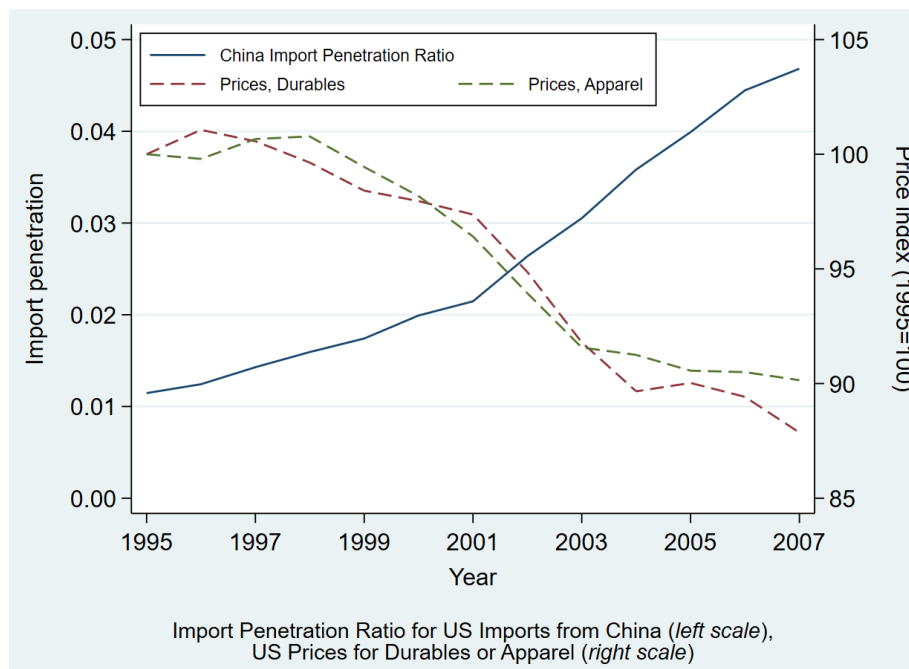
Starting in 2021, two additional treatments were run that took out any occurrence of the word “China” from the narratives and from the accompanying figure:

- **“Trade Hurts Jobs sans China”**: The wording is as follows, with the key change being replacing the description of the rise in imports from China with a description that refers to a general rise in imports into the United States from the rest of the world. “A line of recent research has shown that the United States substantially increased its imports from the rest of the world, as a result of globalization. This was a major force behind the fall in U.S. employment in the manufacturing sector, as the figure below shows. This led to weak wage growth for the middle- and low-income workers who used to hold these manufacturing jobs.”
- **“Trade Helps Jobs sans China”**: The wording is as follows. “A line of recent research has shown that the United States substantially increased its imports from the rest of the world, as a result of globalization. This enabled the U.S. to specialize more in the service sectors in which it is particularly productive, helping to increase the number of jobs in the

U.S. economy. The figure below shows that the rise in total jobs over the last decades was substantial.”

“**Trade Helps Prices**”. Based on price index data from the Bureau of Labor Statistics:

A line of recent research has shown that the United States substantially increased its imports from China, after China joined the World Trade Organization (WTO) in 2001. This was a major force behind the availability of cheaper goods, which benefited Americans. As imports from China increased, the prices of durable goods (computers, electrical products, furniture, etc.) and of nondurable goods such as apparel all saw declines, as the figure below shows.



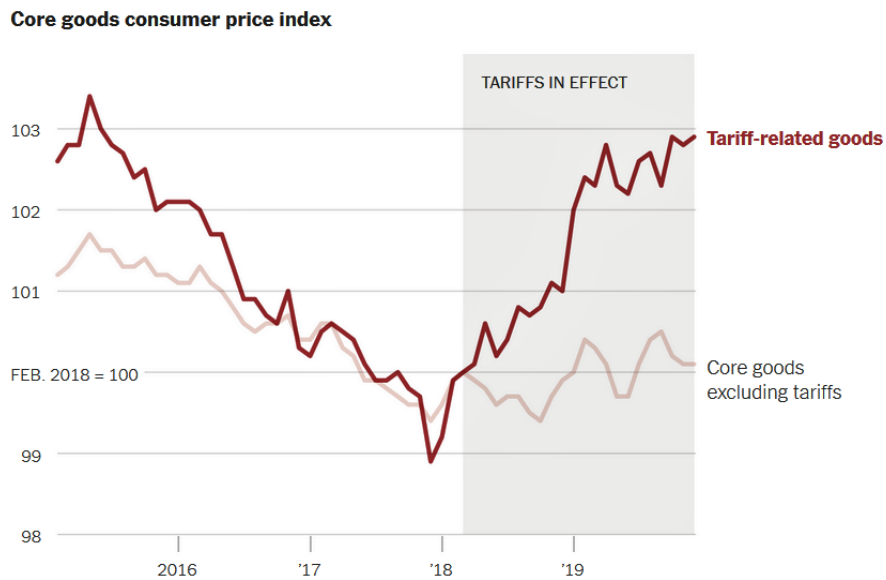
Two variants of the “Trade Helps Prices” treatment were included in the survey starting in 2020:

- **“Trade Helps Prices sans Cheaper”**. The sentence: “This was a major force behind the availability of cheaper goods, which benefited Americans.” was replaced by: “This was a major force behind the increased availability of goods, which benefited Americans.” This wording was intended to replace the adjective “cheaper”, which could have triggered negative views towards imports due to the possible association of “cheaper” with being of “low quality”.
- **“Trade Helps Prices sans China”**. Any references to “China” were removed from the narrative; this parallels the wording in the “Trade Hurts Jobs sans China” and “Trade Helps Jobs sans China” treatments, as follows. “A line of recent research has shown that the United States substantially increased its imports from the rest of the world, as a result of globalization. This was a major force behind the availability of cheaper goods, which

benefited Americans. As imports from the rest of the world increased, the prices of durable goods (computers, electrical products, furniture, etc.) and of nondurable goods such as apparel all saw declines, as the figure below shows.”

“Tariff Hurts Prices”. Based on Amiti, Redding and Weinstein (2019); figure drawn from the *New York Times* (“Opinion: The Year in Charts,” by Steve Rattner, 31 Dec 2019).

A line of recent research has shown that the tariffs in 2018 have raised the cost of living in the United States. Over the course of 2018, the U.S. imposed tariffs on approximately \$400 billion of imports, particularly from China. This led to significant increases in U.S. prices of tariff-related goods, as the figure below shows. It is estimated that this increase in prices lowered U.S. real income by \$1.4 billion per month.



Source: Bureau of Labor Statistics. Core goods excludes food and energy; tariff-related goods prices includes laundry equipment and other appliances, furniture and bedding, housekeeping supplies, window and floor coverings, auto parts and bicycles.

A.2 Full Questionnaire

On the introductory screen, participants are first briefed on the survey, the requirements to participate, the team conducting it, and are given contact information in the event that they have questions. It is mentioned that they can withdraw from the survey at any point, but will only be compensated upon completing the survey. They are then asked if they consent to being surveyed for the project.

Questions asked in the survey are below. Answer choices for each question are in *italics*.

Demographic Questions

- What is your age (in years)?
18-24; 25-34; 35-44; 45-54; 55-64; Above 65
- What gender do you identify with?
Male; Female; Other
- Were you born in the US?
Yes; No
- In which state were you born? (*Dropdown list provided.*)
- In which country were you born? (*Dropdown list provided.*)
- In which state (or territory) do you live? (*Dropdown list provided.*)
- What is the name of the city or town in which you live? (*Text box.*)
- How would you describe your ethnicity/race?
White; African-American; Hispanic, Latino or Spanish origin; Asian; American Indian or Alaskan Native; Middle Eastern or North African; Pacific Islander; Other
- What is your level of education?
High school or less; Some college (or currently in college); College graduate; Post graduate
- What is/was your major in college? (*Dropdown list provided.*)
- Which of the following best describes your employment status?
Employed, working 40 or more hours per week; Employed, working 1-39 hours per week; Not employed, looking for work; Not employed, NOT looking for work; Retired; Disabled, not able to work; Student, full-time
- Which of the following best describes the sector in which you are currently working?
Agriculture; Mining; Manufacturing; Services
- Which of the following best describes your current occupation? (*Dropdown list provided.*)
- What was your TOTAL household income last year?
\$0-\$24,999; \$25,000-\$49,999; \$50,000-\$74,999; \$75,000-\$99,999; \$100,000-\$149,999; \$150,000-\$199,999; \$200,000+; Unsure

Background Views and Beliefs

- On economic policy matters, where do you see yourself on the liberal/conservative spectrum?
More conservative; More liberal; Moderate
- Which party's candidate did you support in the 2016 U.S. presidential election?
Democrat; Republican; Neither
- Which party's candidate did you support in the 2020 U.S. presidential election? [Rounds 3-4 only]
Democrat; Republican; Neither
- When there is an economic policy problem, do you view the free market or government action as the best solution?
Free market; Government action; It depends
- Do you think top income tax rates for the richest households in the United States were higher in the 1980s and the 1990s than they are today?
Yes; No
- How big of a problem do you think inequality is in the United States today?
Not a problem; A small problem; A problem; A serious problem
- Do you think income inequality in the United States has increased or decreased since the 1980s?
Increased; Stayed the same; Decreased
- What do you think the current average tariff rate is in the U.S.? (Tariff rate refers to a tax imposed on imported goods.)
0-4.99%; 5-9.99%; 10-14.99%; 15%+
- Do you think China is one of the top three export destinations for U.S. firms?
Yes; No
- How much of the time do you think you can trust government to do what is right?
Always; Most of the time; About half the time; Sometimes; Never
- How much of the time do you think you can trust private corporations to do what is right for their workers? [Rounds 2-4 only]
Always; Most of the time; About half the time; Sometimes; Never
- How much of the time do you think people in your neighborhood can be trusted? [Rounds 2-4 only]
Always; Most of the time; About half the time; Sometimes; Never
- How much of the time do you think foreigners can be trusted? [Rounds 2-4 only]
Always; Most of the time; About half the time; Sometimes; Never
- Are you willing to pay more for a U.S. brand than a foreign brand of similar quality?
Yes; No
- Which of the following would you prefer on your monthly cell phone statement: Avoiding an additional surcharge of \$100 vs getting a discount of \$100? [Rounds 2-4 only]

Strongly prefer avoiding a surcharge; Slightly prefer avoiding a surcharge; No preference for either; Slightly prefer getting a discount; Strongly prefer getting a discount

- Suppose you are given a cell phone with a market value around \$500. [Rounds 2-4 only]
 - Indicate the price you would be willing to pay if you had to purchase the cell phone yourself:
\$450 or less; Between \$450 and \$500; Exactly \$500; Between \$500 and \$550; \$550 or more
 - Indicate the price you would be willing to accept if you were to sell the cell phone:
\$450 or less; Between \$450 and \$500; Exactly \$500; Between \$500 and \$550; \$550 or more
- Are you satisfied with the current health of the U.S. job market?
Yes; No
- Which of the following best describes how you view your job? [Rounds 2-4 only]
Gives a sense of identity; Just something to do for a living
- How big of a problem do you think inflation (i.e., rising prices) is in the United States today? [Round 4 only]
Not a problem; A small problem; A problem; A serious problem
- What impact do you think the North American Free Trade Agreement (NAFTA, a free trade agreement between the U.S., Mexico, and Canada) has had on you and your family?
Extremely good; Somewhat good; Neither good nor bad; Somewhat bad; Extremely bad
- What impact do you think the coronavirus (covid-19) pandemic has had on job security for you and your family? [Rounds 3-4 only]
Extremely good; Somewhat good; Neither good nor bad; Somewhat bad; Extremely bad
- What impact do you think the U.S. government's coronavirus (covid-19) relief packages and stimulus checks have had for you and your family? [Rounds 3-4 only]
Extremely good; Somewhat good; Neither good nor bad; Somewhat bad; Extremely bad
- Do you approve or disapprove of the U.S. government's coronavirus (covid-19) relief packages and stimulus checks? [Rounds 3-4 only]
Strongly approve; Somewhat approve; Neither approve; nor disapprove; Somewhat disapprove; Strongly disapprove
- Do you agree or disagree with the following statement? Children born into my community will have a better life than my generation.
Strongly agree; Somewhat agree; Neither agree nor disagree Somewhat disagree; Strongly disagree

News Sources

- What type of media would you say is your main source of news about current events?
Television; Internet; Print media/Newspapers; Radio; Podcasts; Word of mouth; None/Don't follow the news

- How often do you follow the news to keep up with current events?
Daily; 3-6 times a week; 1-2 times a week; Less than once a week
- Which of the following programs is your main source of news?
Broadcast television news (e.g., PBS, CBS, ABC, NBC); Cable news: CNN, MSNBC; Cable news: Fox News; Local TV news station; News/Evening news (non-specific); Other specific program/channel
- Which of the following internet sources is your main provider of news?
Commercial media websites (e.g., cnn.com, bbc.com, nytimes.com); Social media (Facebook/Twitter); News aggregating service (Google News, Apple News, etc); Others; None (Do not obtain your news from internet sources)

Information Treatments

Refer to Section A.1 for a description of the information treatments. At the end of the treatment screen (which is a blank screen for the control group), participants are instructed to click to proceed to the next section.

Treatment Response Questions

- What impact do you think being open to international trade has had for most Americans?
[Rounds 2-4 only]
Extremely good; Somewhat good; Neither good nor bad; Somewhat bad; Extremely bad
- How confident are you in your assessment from the previous question, regarding the impact that international trade has had for most Americans? [Rounds 2-4 only]
Not at all confident; Somewhat not confident; Neutral; Somewhat confident; Extremely confident
- Do you support placing more limits on imports?
Yes; No
 - If yes, on which countries?
All Countries; Developing countries; Others (text box to specify)
- Would you support an increase in the U.S. tariff rate to reduce imports?
Yes; No, maintain tariff rate; No, lower tariff rate
- What would you like the U.S. tariff rate to be? *(Text box.)*
- Should the U.S. tariff rate on imports be increased for specific industries?
Yes; No
 - If yes, on which industries? *(Text box.)*
- Would you like the U.S. to leave the North American Free Trade Agreement (NAFTA, a free trade agreement between the U.S., Mexico, and Canada)?
Yes; No

- Would you support a higher minimum wage?
Yes; No
- Of the following two policies, which do you prefer?
Higher taxes on top income earners; Higher tariff rates on imports from foreign countries; Both policies; Neither policy
- Would you support the U.S. signing free trade agreements with more foreign countries?
Yes; No
- Of the policies listed below, please select the three you MOST prefer: (*order randomized for survey participants*)
 - *More limits on imports from foreign countries (e.g., higher tariffs on imports)*
 - *Exiting from existing free trade agreements*
 - *Higher taxes on top income earners*
 - *More benefits for the unemployed (e.g., unemployment insurance)*
 - *More limits on immigration*
 - *Improving education and worker training*
 - *Weakening the U.S. dollar, so that U.S. exports are more competitive*
 - *Higher minimum wage*
- Of the policies listed below, please select the three you LEAST prefer: (*order randomized for survey participants*)
 - *More limits on imports from foreign countries (e.g., higher tariffs on imports)*
 - *Exiting from existing free trade agreements*
 - *Higher taxes on top income earners*
 - *More benefits for the unemployed (e.g., unemployment insurance)*
 - *More limits on immigration*
 - *Improving education and worker training*
 - *Weakening the U.S. dollar, so that U.S. exports are more competitive*
 - *Higher minimum wage*

Validation and Follow-up

- Did the information from the research findings that you read about earlier in this survey affect your views on trade policy (i.e., the use of tariffs or limits on imports)? [Rounds 2-4 only]
Strongly agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Strongly disagree
- If participant selected “More Limits on Imports” as one of their three “Most Preferred” policies, they were directed to a series of follow-up questions. [Rounds 3-4 only]

- For participants in the control group: “We noticed that you selected “More limits on imports” as one of your three most preferred policies. For each of the following statements, please tell us the degree to which it explains your selecting “More limits on imports” as a preferred policy. I selected “More limits on imports” as a preferred policy because. . .” (*order randomized for survey participants*)

- * Imports are often of lower quality.
- * Imports often compete for jobs with U.S. workers.
- * Imports are a potential threat to U.S. national security.
- * I am concerned about U.S. imports from countries such as China.
- * There are other more important concerns.

For each potential reason, the participant chooses between the following options:

Strongly agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Strongly disagree

- For participants in the “Trade Hurts Jobs” or “Trade Hurts Jobs sans China” treatment groups: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how imports have affected manufacturing jobs in the U.S.” Also, the following potential reason is added to the baseline list: (*order randomized*)

- * I was persuaded that imports have hurt jobs in the U.S.

- For participants in the “Trade Helps Jobs” or “Trade Helps Jobs sans China” treatment groups: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how trade has allowed the U.S. to create jobs in the service sectors in which the U.S. is particularly productive.” Also, the following potential reason is added to the baseline list: (*order randomized*)

- * I was not persuaded that trade has helped to create jobs in the U.S.

- For participants in the “Trade Hurts Helps Jobs” treatment group: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how imports have affected manufacturing jobs in the U.S., while at the same time trade has allowed the U.S. to create jobs in the service sectors in which the U.S. is particularly productive.” Also, the following potential reason is added to the baseline list: (*order randomized*)

- * I was not persuaded that trade has helped to create jobs in the U.S.

- For participants in the “Trade Helps Hurts Jobs” treatment group: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how trade has allowed the U.S. to create jobs in the service sectors in which the U.S. is particularly productive, while at the same time imports have affected manufacturing

jobs in the U.S.” Also, the following potential reason is added to the baseline list: *(order randomized)*

* I was not persuaded that trade has helped to create jobs in the U.S.

- For participants in the “Trade Helps Prices”, “Trade Helps Prices sans China”, and “Trade Helps Prices sans Cheaper” treatment groups: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how imports have helped to lower prices of goods for Americans.” Also, the following potential reason is added to the baseline list: *(order randomized)*

* I was not persuaded that imports have lowered goods prices for Americans.

- For participants in the “Tariff Hurts Prices” treatment groups: The opening sentence is replaced by “We noticed that you selected “More limits on imports” as one of your three most preferred policies, after reading the information about how tariffs imposed by the U.S. have raised the prices of goods for Americans.” Also, the following potential reason is added to the baseline list: *(order randomized)*

* I was not persuaded that tariffs imposed by the U.S. have raised goods prices for Americans.

- For all the above groups: What other reasons led you to select “More limits on imports” as a preferred policy? *(Text box.)*

- Has the coronavirus (covid-19) pandemic affected your views on trade policy (i.e., the use of tariffs or limits on imports)? [Rounds 2-4 only]

Yes; No

- In view of the coronavirus (covid-19) pandemic, which of the following would you agree with? (Select all that apply.) [Rounds 2-4 only]

Yes; No

- *Countries should be able to restrict the export of medical products and health equipment.*
- *Countries should avoid imposing tariffs on imports of medical products and health equipment.*
- *Countries should keep the manufacture of goods that are needed in supply chains at home and avoid moving production abroad.*
- *Countries should avoid imposing tariffs on imports of goods that are needed in supply chains.*
- *Countries should be able to restrict the movement of people across borders.*
- *None of the above.*

- How has the coronavirus (covid-19) pandemic affected your views of China? [Rounds 3-4 only]

Strongly positively affected; Somewhat positively affected; Neither positively nor negatively affected; Somewhat negatively affected; Strongly negatively affected

- In what other ways has the coronavirus (covid-19) pandemic affected your views about globalization? [Rounds 2-4 only] (*Text box.*)
- The information from the research findings that I read about earlier in this survey was on the topic of: [Rounds 2-4 only] (*order randomized*)
 - *the relationship between trade and prices*
 - *the relationship between trade and jobs*
 - *I did not receive information on any of the above*

A.3 Appendix Tables and Figures

In this section, we provide a walk-through guide of the appendix tables and figures.

In Appendix Tables 1a-1e, we report summary statistics for a host of respondent characteristics and survey features separately for the control and each treatment group; these are presented for round 1 in Appendix Table 1a, round 2 in Appendix Table 1b, round 3 in Appendix Table 1c, and round 4 in Appendix Tables 1d-1e. These illustrate that the underlying treatment randomization delivered subsamples that were broadly balanced along these baseline characteristics. The respective table footnotes report p-values for a randomization-t multiple hypothesis test (based on Young 2019) of the orthogonality of the covariates.

In Appendix Table 2, we elaborate on the regressions presented in Table 4 of the main paper, which are based on the pooled rounds 2-4 data. Column 1 in this appendix table reports a stripped-down version of the baseline regression from Column 6 of Table 4 (where the dependent variable is the first principal component measure of preferences for protection); we remove all auxiliary controls here to verify that the treatment effects remain relevant. Column 2 reproduces Column 6 of Table 4 in its entirety, reporting the full set of coefficients for the controls. Columns 3 and 4 report on the full set of estimated marginal effects from Columns 7 and 8 of Table 4 (ordered logit regressions), which are based respectively on the survey question asking respondents if the information affected their views on trade policy (1= Strongly disagree, 5=Strongly agree), and their assessment of the impact of trade on most Americans (1= Extremely bad, 5=Extremely good).

In Appendix Table 3, we present robustness checks based on different samples and alternative constructions of the dependent variable. Using the first principal component outcome measure, Columns 1-3 present the regressions when run separately on rounds 2, 3, and 4 respectively. Column 4 pools all four rounds of data. Columns 5-7 revert to the pooled rounds 2-4 sample, and instead aggregate the five component questions via respectively a simple unweighted average, a dummy equal to one if the respondent selected a protectionist response on at least three of the five component variables, and the first factor based on a factor analysis of the five variables. (Note that we subtract the response to the question on support for more free trade agreements from one, to obtain outcome measures that are increasing in protectionist preferences.)

In Appendix Table 4, we reproduce the specifications from Table 4 in our main paper, but now jointly estimate the effects of the four baseline treatments along with that of all variants of the information treatments, using all available observations from rounds 2-4. In the additional Column 9, the dependent variable is the ordered categorical measure of respondents' confidence (1=Not at all confident, 5=Extremely confident) in their assessment of the impact that trade has had for most Americans, this being the outcome variable in the preceding Column 8.

Appendix Table 5 reports summary statistics related to the end-of-survey information recall question. This includes the share of respondents who selected each answer option ("about jobs", "about prices", "no information"), as well as the shares who conditional on the information received were able to correctly recall it.

Appendix Table 6 demonstrates the robustness of the Table 4, Column 6 baseline specification to controlling for two key shocks that were contemporaneous to round 2 of the survey. We use a

county-by-week measure of mobility from Safegraph, that is based on cell-phone signals around local points of interest, to capture the severity of Covid-19 lockdowns during the first months of the pandemic; Column 1 incorporates an indicator variable equal to 1 for observations with a below-median Safegraph mobility score. We include in Column 2 a dummy variable for whether a Black Lives Matters event was reported in a given county-week, drawn from the ACLED project database. Last but not least, Column 3 jointly controls for both of these shock dummies.

Appendix Table 7 examines the interplay between the duration spent on the treatment screen (a proxy for attention), the accuracy of information recall, and protectionist preferences. As a reminder, Columns 2-4 of Table 7 in the main paper estimated the treatment effects for respondents who spent: (i) below median; (ii) above median; and (iii) top quintile duration on their respective treatment screens by survey round. Appendix Table 7 further subdivides these treated respondents into those who incorrectly recalled whether the information was about jobs or prices (Panel A), and those with correct recall (Panel B); in both panels, the control group includes all respondents who did not receive any information (since absent a treatment, the measures of treatment duration and recall accuracy are not as meaningful). Within each subset of respondents (i.e., “Recall incorrect” and “Recall correct”), we find once again that those who spent a longer time on the treatment screen appear to update their policy preferences in the direction of the information, becoming more strongly in favor of limits on trade if they received the “Trade Hurts Jobs” narrative, and less so if they received the “Trade Helps Jobs”, “Trade Helps Prices” or “Tariff Hurts Prices” narratives. Interestingly, the estimates in Column 1 of Panels A and B indicate that the backfire effect to information on the beneficial effect of trade on prices (or the harmful effect of tariffs) is quite pervasive, in that this appears regardless of whether the respondents correctly identified the narrative as being about “prices” per se.

In Appendix Tables 8-10, we provide more detail on the regressions in which we interact the treatment dummies with respondent characteristics, following the specification in equation (3) in the main text. The interaction coefficients were illustrated in Figure 2 in the main paper. In these appendix tables, we report the estimated level effects of the treatment dummies, the respondent characteristic under consideration, and the interaction coefficients.

Appendix Table 8 presents these for the six measures of economic self-interest we considered: whether the individual is employed in the manufacturing sector (Column 1); the Autor et al. (2013) China import shock measure for 2000-2007 at the commuting zone level (Column 2); whether the individual has less-than-college educational attainment (Column 3); whether the respondent is currently unemployed (Column 4); whether the respondents’ annual household income was less than \$50,000 (Column 5); and the respondent’s assessment of how bad NAFTA has been for them and their family (1=Extremely good, 5=Extremely bad; Column 6).

Appendix Table 9 presents these for the six measures of sociotropic concerns: whether the individual views inequality in the U.S. to be a problem (1=Not a problem, 4=A serious problem; Column 1); whether the individual views inflation in the U.S. to be a problem (1=Not a problem, 4=A serious problem, available in round 4 only; Column 2); degree of trust in government “to do what is right” (1=Never, 5=Always; Column 3); whether the respondent is willing to pay more for a U.S. brand of similar quality (Column 4); whether the respondent is dissatisfied with the current state of the U.S. job market (Column 5); and the respondents’ extent of disagreement

with the statement that “children born into my community will have a better life than my generation” (1=Strongly agree, 5=Strongly disagree; Column 6).

Appendix Table 10 reports these regressions for: the measure of loss aversion (1=Strongly prefer getting a discount of \$100, 5=Strongly prefer avoiding a surcharge of \$100; Column 1); whether the respondent supported the Republican party candidate in the most recent presidential election (Column 2); and whether the respondent supported the Democratic party candidate in the most recent presidential election (Column 3).

Appendix Table 11 analyzes the agreement scores that respondents expressed with each of the listed reasons for selecting “more limits on imports” as a “Most Preferred” policy, when directed to this set of follow-up questions. The dependent variable is the agreement score (on an integer scale of 1 to 5) of respondent i with reason r , where $r = 0, 1, \dots, 5$. The table is based on the OLS specification with respondent fixed effects in equation (4) in Section 6.3 of the main paper. “Imports often compete for jobs with U.S. workers” and “I am concerned about U.S. imports from countries such as China” received the highest agreement scores. These were significantly higher than the agreement scores recorded on the other listed reasons (namely: persuaded/not persuaded, quality, national security, and other concerns); looking across all columns, the p-values for the relevant coefficient comparisons range between 0.000 and 0.053. Note here that Column 1 pools respondents across all control and treatment groups, while Columns 2-10 restrict the regression sample to the treatment groups indicated in the respective column headings (these are the respective subsets of respondents that correspond to each row in Table 8).

In Appendix Table 12, we present logit regressions that test for whether there are differences across the information treatment groups in the propensity for respondents to mention “China” in their textual answers. The dependent variable in Columns 1-2 is an indicator for whether “China” is listed as a text answer to the question on which countries they would favor placing more import limits on, while that in Columns 3-4 is an indicator for whether “China” is mentioned in the textual response on other reasons for selecting “more limits on imports” as a “Most Preferred” policy; the latter variable is naturally defined only for the subset of respondents who made this a top-three policy choice. The sample in Columns 1 and 3 comprises the control, “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and their counterpart “sans China” treatment groups; the sample in Columns 2 and 4 comprises all available observations in rounds 2-4. We verify that there is no difference in the propensity to mention “China” across the control, “with China”, and “sans China” treatment groups.

In Columns 5-6, we present logit regressions that explore whether there are differences in the propensity to mention the word “jobs” in the free text box response to the question seeking other reasons for selecting “more limits on imports” as a top-three preferred policy. Column 5 restricts the sample to the control, “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and their counterpart “sans China” treatment groups, while Column 6 uses all available observations from rounds 2-4. The results show that there is no significant difference in the propensity for “jobs” to be mentioned across the control group, jobs-related treatment groups, and price-related treatment groups. (Note that we control in this regression table for survey round dummies *in lieu* of week dummies due to the more limited number of observations with text responses.)

Appendix Table 13 explores if there are differences in the treatment effects from “with China”

versus “sans China” versions of what would otherwise be the same narrative. The dependent variables we consider are the first principal component measure of protectionist preferences (Column 1); self-declared responses to whether the information affected views on trade policy (Column 2); and one’s assessment on the impact that trade has had for most Americans (Column 3). Each panel is run on a sample that comprises the control group and the listed pair of “with China” and “sans China” treatments. Focusing on Column 1, we find that both the “Trade Hurts Jobs” treatment and the variant of it that omits mentioning China exhibit a positive and significant effect on preferences for protection (Panel A). The treatment effects are likewise positive, though marginally insignificant, for the “Trade Helps Jobs” and its “sans China” variant (Panel B). Both the “Trade Helps Prices” and “Trade Helps Prices sans China” treatments also provoke a similar protectionist response (Panel C). Importantly, we find throughout the table that the effects of the “with China” and “sans China” treatments are statistically indistinguishable.

Appendix Table 14 returns to the agreement scores with the listed reasons for selecting “more limits on imports” as a “Most Preferred” policy. We perform a comparison of these agreement scores for respondents from each “with China” treatment group vis-à-vis the corresponding “sans China” counterpart treatment group. The samples in Columns 1-2 comprise the participants who received either the “Trade Hurts Jobs” or “Trade Hurts Jobs sans China” treatments, with “I was persuaded that imports have hurt jobs in the U.S.” being the omitted reason category. The sample in Columns 3-4 comprises the “Trade Helps Jobs” and its “sans China” variant, while that in Columns 5-6 comprises the “Trade Helps Prices” and its “sans China” variant; the omitted category in these columns is “I was not persuaded”. Each even-numbered column examines whether there were differences in the propensity to agree with a particular reason across the “with China” and “sans China” versions of the same narrative. Note that there is no statistically significant difference in the agreement scores for concerns about American jobs and concerns about trade with China, with one exception. (For “Trade Helps Prices”, respondents who received the “with China” narrative expressed stronger agreement with concerns about trade with China than those who received the “sans China” narrative.)

Appendix Figures 1 and 2 are the analogues of Figures 1 and 2 in the main paper, that are constructed by using all rounds 2-4 respondents in the control, “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” groups, rather than restricting to those who spent an above-median duration on the treatment screen. These figures respectively illustrate the level effects and the interaction coefficients of each covariate.

Appendix Figure 3 presents additional word clouds. Panel A illustrates text responses on other reasons for choosing “more limits on imports” as a “Most Preferred” policy, separately for respondents who received a “with China” treatment (“Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, on the left) and for the three respective “sans China” narratives (on the right). Panel B illustrates text responses for the countries the participant would support placing more import limits on. This is shown separately for those who received a jobs-related treatment (“Trade Hurts Jobs”, “Trade Helps Jobs”, and their “sans China” variants, on the left), and for those who received a prices-related treatment (“Trade Helps Prices” and its “sans China” variant, on the right).

A.4 Model: Belief Updating on Preferences for Protection

We present the details of the model of belief updating in the formation of trade policy preferences, described earlier in Section 6.1 in the main paper. Recall that one of the goals of the model is to derive an empirical specification to examine how the information treatments affect preferences for protection in a setting with non-Bayesian belief updating.

Consider a stylized setting in which there are two possible trade policies: “*FT*” in which free trade is adopted, and “*LT*” where limits on trade are put in place. We consider the decision problem from the perspective of individuals, indexed by i . Let A refer to the “state” that free trade is good (equivalently, that limits on trade are bad). Individual i places a (prior) probability $p_i(A)$ on the realization of this state that free trade is good. On the other hand, A^c denotes the “state” that free trade is bad (equivalently, that limits on trade are good), which holds with complementary probability $1 - p_i(A)$.

Individual i 's expected utility under *FT* is given by:

$$U_i(FT) = p_i(A)U_i(FT|A) + (1 - p_i(A))U_i(FT|A^c) + \varepsilon_{i,FT},$$

where $U_i(FT|A)$ and $U_i(FT|A^c)$ are the levels of utility experienced by the individual under free trade, conditional on the realization of the states A (“free trade is good”) and A^c (“free trade is bad”) respectively. $\varepsilon_{i,FT}$ is a preference shock term, that is an iid draw across individuals i taken from a Gumbel distribution with zero location parameter and unit shape parameter.

On the other hand, the individual's expected utility under *LT* is given by:

$$U_i(LT) = p_i(A)U_i(LT|A) + (1 - p_i(A))U_i(LT|A^c) + \varepsilon_{i,LT},$$

where $U_i(LT|A)$ and $U_i(LT|A^c)$ are the analogously defined utility levels of individual i if limits to trade are enacted. $\varepsilon_{i,LT}$ is an iid shock drawn from a separate Gumbel distribution with zero location parameter and unit shape parameter; this is independent in particular from the $\varepsilon_{i,FT}$'s. We assume that individuals are aware of the distributions from which $\varepsilon_{i,FT}$ and $\varepsilon_{i,LT}$ are drawn, but are unaware of the actual realizations of these draws at the time they express their preferences over *FT* versus *LT*.

It will be convenient to define: $\Delta U_{i,FT} \equiv U_i(FT|A) - U_i(LT|A)$ and $\Delta U_{i,LT} \equiv U_i(LT|A^c) - U_i(FT|A^c)$, while making the natural assumption that: $\Delta U_{i,FT}, \Delta U_{i,LT} > 0$. In words, conditional on “trade is good”, the individual's utility is higher under free trade than under limits on trade. Likewise, conditional on trade being “bad”, their utility is higher if there are limits on trade rather than under free trade.

Individual i would prefer more limits on imports if $U_i(FT) < U_i(LT)$. The probability that this occurs is:

$$\begin{aligned} Pr(U_i(FT) < U_i(LT)) &= Pr(\varepsilon_{i,FT} - \varepsilon_{i,LT} < -p_i(A)\Delta U_{i,FT} + (1 - p_i(A))\Delta U_{i,LT}) \\ &= \frac{\exp\{-p_i(A)\Delta U_{i,FT} + (1 - p_i(A))\Delta U_{i,LT}\}}{1 + \exp\{-p_i(A)\Delta U_{i,FT} + (1 - p_i(A))\Delta U_{i,LT}\}}. \end{aligned}$$

where we use the property that $\varepsilon_{i,FT} - \varepsilon_{i,NFT}$ takes on a logistic distribution with mean zero and

unit scale parameter. Bearing in mind that $\Delta U_{i,FT}, \Delta U_{i,LT} > 0$, the above expression implies that the individual is more disposed to prefer limits on trade if: (i) the perceived probability that free trade is good, $p_i(A)$, is smaller; (ii) the utility gap across A^c and A under limits on trade, $\Delta U_{i,LT}$, is larger; and (iii) the utility gap across A and A^c under free trade, $\Delta U_{i,FT}$, is smaller.

Suppose that individuals adopt a cutoff rule whereby they express a preference for limits on trade if $Pr(U_i(FT) < U_i(LT))$ is sufficiently high. We normalize this cutoff probability to 1/2, so that a preference for limits on trade is voiced if there is a higher probability that one will be better off under LT than under FT ; the cutoff of 1/2 is algebraically convenient, but is without loss of generality as long as the cutoff is a constant. Define y_i to be an indicator variable equal to 1 if i expresses a preference for limits on trade, and equal to 0 otherwise. We thus have:

$$\begin{aligned} y_i &= \mathbf{1} \left(Pr(U_i(FT) < U_i(LT)) > \frac{1}{2} \right) = \mathbf{1} \left(\log \frac{Pr(U_i(FT) < U_i(LT))}{1 - Pr(U_i(FT) < U_i(LT))} > 0 \right) \\ &= \mathbf{1} \left(\log \frac{1 - p_i(A)}{p_i(A)} + \log \frac{\Delta U_{i,LT}}{\Delta U_{i,FT}} > 0 \right). \end{aligned} \quad (\text{A.1})$$

We now map (A.1) to our data setting, by positing that our first principal component dependent variable of preferences for protection is a monotone increasing function of y_i . This rationalizes a specification in which we regress this outcome variable against an empirical counterpart for $\log \frac{1 - p_i(A)}{p_i(A)} + \log \frac{\Delta U_{i,LT}}{\Delta U_{i,FT}}$. For individuals in the no-information control group, the $p_i(A)$ that they use in this decision problem is the probability based on prior beliefs that they attach to “trade is good” being the realized state. For individuals who receive an information treatment, the content of this treatment communicates a signal S about whether trade is good or bad. Whether or not the individual expresses a preference for limits on imports then depends not on the prior probability, but on the posterior probability after beliefs are updated, which we denote by $\pi_i(A|S)$. In other words, we replace $\frac{1 - p_i(A)}{p_i(A)}$ by $\frac{1 - \pi_i(A|S)}{\pi_i(A|S)}$ in equation (A.1).

We adopt the formulation of generalized belief updating from Charness and Dave (2017) and Benjamin (2019), where the posterior odds of A^c relative to A conditional on receiving a treatment narrative S are given by:

$$\frac{1 - \pi_i(A|S)}{\pi_i(A|S)} = \left(\frac{p(S|A^c)}{p(S|A)} \right)^{\kappa_S} \frac{1 - p_i(A)}{p_i(A)}. \quad (\text{A.2})$$

In particular, the case $\kappa_S = 1$ corresponds to Bayes rule. More broadly, we consider a form of non-Bayesian updating that is “prior-biased” (Benjamin 2019), wherein:

$$\kappa_S = c_{0,S} + c_{1,S}(\mathbf{1}(S \text{ confirms } A^c)) + c_{2,S}(\mathbf{1}(S \text{ disconfirms } A^c)),$$

with $c_{0,S} + c_{1,S} > 0$ and $c_{0,S} + c_{2,S} < 0$. (We allow the magnitude of these coefficients to differ with S to allow for heterogeneity in the strength of updating across different treatments, subject to the sign restrictions being respected.)

Note that $\frac{p(S|A^c)}{p(S|A)}$ is the relative likelihood of observing the signal S under the state “trade is bad” versus “trade is good”. It is natural to assume that $\frac{p(S|A^c)}{p(S|A)} > 1$ for information treatments that convey a negative impact of openness to trade (e.g., “Trade Hurts Jobs”), so that

it is more likely that one would observe such a signal in the state A^c where “trade is bad”; conversely, we have $\frac{p(S|A^c)}{p(S|A)} < 1$ for information treatments that communicate a positive benefit from trade (e.g., “Trade Helps Jobs”, “Trade Helps Prices”). S is then said to “confirm” A^c if both $\frac{p(S|A^c)}{p(S|A)}, \frac{1-p_i(A)}{p_i(A)} > 1$ or both $\frac{p(S|A^c)}{p(S|A)}, \frac{1-p_i(A)}{p_i(A)} < 1$. On the other hand, S is said to “disconfirm” A^c if either $\frac{p(S|A^c)}{p(S|A)} > 1 > \frac{1-p_i(A)}{p_i(A)}$ or $\frac{1-p_i(A)}{p_i(A)} > 1 > \frac{p(S|A^c)}{p(S|A)}$.

To see how the belief updating process in (A.2) operates, consider the case of an individual i who places a higher prior probability on free trade being bad rather than good (i.e., $\frac{1-p_i(A)}{p_i(A)} > 1$). We refer (for simplicity) to such as an individual as having a prior belief that free trade is bad; in the context of political identity that we discuss in the main paper, this would be because the individual identifies as a Republican supporter. Then:

- If S is the information treatment that “Trade Hurts Jobs”, the signal S confirms their prior ($\frac{p(S|A^c)}{p(S|A)} > 1$). Since $\kappa_S = c_{0,S} + c_{1,S} > 0$, (A.2) implies that the individual updates toward their prior: $\frac{1-\pi(A|S)}{\pi(A|S)} > \frac{1-p(A)}{p(A)} > 1$, so this reinforces their belief that “trade is bad”.
- If S is instead the information treatment that “Trade Helps Jobs” or “Trade Helps Prices”, this signal S disconfirms their prior ($\frac{p(S|A^c)}{p(S|A)} < 1$). Since $\kappa_S = c_{0,S} + c_{2,S} < 0$, we have: $\left(\frac{p(S|A^c)}{p(S|A)}\right)^{\kappa_S} > 1$. From (A.2), this implies: $\frac{1-\pi(A|S)}{\pi(A|S)} > \frac{1-p(A)}{p(A)} > 1$ once again. The individual thus updates in a manner that doubles down on their prior belief that “trade is bad” in the face of this discordant signal.

The above discussion also applies analogously for individuals who identify as Democrat (with the opposite prior beliefs $\frac{1-p_i(A)}{p_i(A)} < 1$). This specification of κ_S therefore implies that belief updating is “prior-biased” in that the individual updates in the direction of their prior regardless of whether the signal is confirming or disconfirming of their baseline beliefs.

Substituting from (A.2) into (A.1), we see that a preference is expressed for more limits on imports ($y_i = 1$) if and only if: $\kappa_S \log \frac{p(S|A^c)}{p(S|A)} + \log \frac{1-p_i(A)}{p_i(A)} + \log \frac{\Delta U_{i,LT}}{\Delta U_{i,FT}} > 0$. Bearing in mind the earlier discussion on mapping to the empirical variables, this calls for regressing our measure of preferences for protection on $\kappa_S \log \frac{p(S|A^c)}{p(S|A)} + \log \frac{1-p_i(A)}{p_i(A)} + \log \frac{\Delta U_{i,LT}}{\Delta U_{i,FT}}$; the latter can be re-written as:

$$\begin{aligned} & \log \frac{1-p_i(A)}{p_i(A)} + \log \frac{\Delta U_{i,LT}}{\Delta U_{i,FT}} + c_{0,S} \log \frac{p(S|A^c)}{p(S|A)} \\ & + \left[c_{1,S} \mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} > 1 \right) + c_{2,S} \mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} < 1 \right) \right] \mathbf{1} \left(\frac{p(S|A^c)}{p(S|A)} > 1 \right) \log \frac{p(S|A^c)}{p(S|A)} \\ & + \left[c_{1,S} \mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} < 1 \right) + c_{2,S} \mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} > 1 \right) \right] \mathbf{1} \left(\frac{p(S|A^c)}{p(S|A)} < 1 \right) \log \frac{p(S|A^c)}{p(S|A)} \end{aligned}$$

For a given signal S , the above implies that the effect of the information treatment is potentially heterogeneous across individuals in a manner that depends on their priors, as captured by the $\mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} > 1 \right)$ and $\mathbf{1} \left(\frac{1-p_i(A)}{p_i(A)} < 1 \right)$ terms. Consider for example the “Trade Hurts Jobs” signal. The above expression calls for the use of a treatment dummy to pick up the main effect of the treatment (the term in $\log \frac{p(S|A^c)}{p(S|A)}$, with coefficient $c_{0,S}$), while including interactions

of this dummy with respondent variables that pick up whether or not the individual in question has a prior that is aligned with the signal (i.e., $\mathbf{1}\left(\frac{1-p_i(A)}{p_i(A)} > 1\right)$) or discordant with it (i.e., $\mathbf{1}\left(\frac{1-p_i(A)}{p_i(A)} < 1\right)$); for example, these could respectively be a Republican and Democrat supporter dummy, and the implied interaction coefficients would be $c_{1,S}$ and $c_{2,S}$. The sign restrictions $c_{0,S} + c_{1,S} > 0$ and $c_{0,S} + c_{2,S} < 0$ in turn mean that $c_{1,S} > c_{2,S}$. A finding of heterogeneous treatment effects, with $c_{1,S} > c_{2,S}$ – the interaction coefficient on a Republican dummy exceeding that on the Democrat dummy – would thus be consistent with prior-biased updating. Separately, we associate the $\frac{1-p_i(A)}{p_i(A)}$ and $\frac{\Delta U_{i,LT}}{\Delta U_{i,FT}}$ terms on the right-hand side with respondent i control variables cum an error term: $\beta_X X_i + \epsilon_i$.

This discussion yields a rationalization for the interaction specification – equation (3) in the main paper – that we pursue, where we interact the treatment dummies with respondent characteristics, x_i , that are potential markers of one’s priors toward protectionist policies. It moreover provides an interpretation of those interaction coefficients through the lens of “prior-biased” updating. In practice, we explore a large set of respondent observables, although we ultimately focus most on the political identity dummies given the clear pattern of differential treatment effects and the large effect sizes we find for these variables.

Appendix Table 1a
Treatment Balance: Survey Round 1 (2018-2019)

TREATMENT:	Control	Trade Hurts Jobs	Trade Helps Jobs	Trade Helps Prices
<u>Biodata</u>				
Gender: Male	0.49 [0.50]	0.48 [0.50]	0.50 [0.50]	0.49 [0.50]
Gender: Female	0.50 [0.50]	0.51 [0.50]	0.50 [0.50]	0.50 [0.50]
Age: Average (approx.)	47.14 [17.11]	48.10 [16.78]	47.82 [17.02]	47.17 [16.19]
Race: White	0.60 [0.49]	0.60 [0.49]	0.64 [0.48]	0.62 [0.49]
Race: African-American	0.13 [0.33]	0.11 [0.31]	0.11 [0.32]	0.11 [0.31]
Race: Hispanic	0.15 [0.36]	0.18 [0.38]	0.17 [0.37]	0.18 [0.38]
Born in US?	0.92 [0.28]	0.91 [0.29]	0.93 [0.25]	0.92 [0.27]
<u>Socio-Economic Characteristics</u>				
Household Income: Average \$ (approx.)	56,283 [46,165]	59,436 [49,180]	60,356 [50,360]	56,851 [44,589]
Education: Average years (approx.)	11.84 [4.97]	11.98 [4.87]	11.70 [4.93]	11.73 [4.88]
Employment Status: Not in Labor Force	0.41 [0.49]	0.39 [0.49]	0.38 [0.49]	0.40 [0.49]
Employment Status: Unemployed	0.11 [0.32]	0.09 [0.28]	0.10 [0.30]	0.09 [0.29]
Employment Status: Employed	0.48 [0.50]	0.52 [0.50]	0.52 [0.50]	0.50 [0.50]
Employment Sector: Manufacturing	0.07 [0.26]	0.08 [0.27]	0.08 [0.27]	0.07 [0.25]
Employment Sector: Services	0.36 [0.48]	0.41 [0.49]	0.41 [0.49]	0.40 [0.49]
Student?	0.04 [0.20]	0.03 [0.17]	0.03 [0.16]	0.03 [0.17]
<u>Baseline Socio-Political Attributes</u>				
Last Presidential election: Supported Dem.	0.42 [0.49]	0.41 [0.49]	0.42 [0.49]	0.41 [0.49]
Last Presidential election: Supported Rep.	0.34 [0.48]	0.34 [0.47]	0.34 [0.47]	0.34 [0.48]
Trust in government? (Scale: 1 to 5)	2.42 [1.06]	2.45 [1.10]	2.64 [1.02]	2.51 [1.02]
Impact of NAFTA on family (Scale: 1 to 5)	3.15 [0.89]	3.12 [0.95]	3.18 [0.86]	3.17 [0.88]
Children born into better life? (Scale: 1 to 5)	3.03 [1.09]	3.09 [1.17]	3.08 [1.11]	3.07 [1.14]
Satisfied with health of US job market?	0.46 [0.50]	0.48 [0.50]	0.48 [0.50]	0.52 [0.50]
Willing to pay more for US brand?	0.59 [0.49]	0.59 [0.49]	0.59 [0.49]	0.57 [0.49]
Inequality in US a problem? (Scale: 1 to 4)	3.07 [0.93]	2.94 [1.01]	3.02 [0.93]	3.01 [0.94]
<u>News consumption patterns</u>				
Number of days per week (approx.)	4.90 [2.52]	5.11 [2.47]	5.03 [2.45]	5.02 [2.44]
Main tv source: Broadcast tv	0.26 [0.44]	0.31 [0.46]	0.28 [0.45]	0.29 [0.45]
Main tv source: CNN, MSNBC	0.18 [0.38]	0.17 [0.38]	0.18 [0.38]	0.15 [0.36]
Main tv source: Fox News	0.15 [0.36]	0.14 [0.35]	0.16 [0.37]	0.17 [0.38]
<u>Location Characteristics</u>				
Share with college and above (age>=25)	0.31 [0.11]	0.30 [0.10]	0.30 [0.11]	0.29 [0.11]
Autor-Dorn-Hanson measure for 2000s	2.58 [1.80]	2.50 [1.66]	2.59 [1.83]	2.56 [2.00]
Share of manufacturing in employment	0.16 [0.11]	0.16 [0.11]	0.17 [0.12]	0.17 [0.12]
Urban?	0.89 [0.31]	0.87 [0.34]	0.83 [0.37]	0.84 [0.36]
<u>Survey Characteristics</u>				
Duration to complete (secs.)	594 [571]	619 [406]	936 [2,683]	774 [1,324]
Treatment duration	---	47 [70]	45 [50]	50 [74]
Mobile device?	0.57 [0.50]	0.57 [0.50]	0.65 [0.48]	0.64 [0.48]

Notes: Mean values reported for each control or treatment group, with standard deviations in brackets. For respondent age, household income, and frequency of news consumption, this is approximated by a weighted average of the midpoint values of the response option bins, using the share of respondents picking each bin as weights. For respondent years of education, an analogous weighted average is taken that assigns 6 years to "High school or less", 14 years to "Some college", 16 years to "College graduate", and 18 years to "Post graduate". The randomization-t p-value (c.f., Young 2019) for a multiple hypothesis test of the orthogonality of the above covariates with respect to the Round 1 treatment dummies is 0.864 (based on 1,000 iterations, controlling for survey-week fixed effects); we exclude from the covariate set examined in this test the survey and treatment duration variables (which mechanically differ across treatments), and the male gender and out of labor force dummies (due to collinearity with other variables).

Appendix Table 1b
Treatment Balance: Survey Round 2 (2020)

TREATMENT:	Control	Trade Hurts Jobs	Trade Helps Jobs	Trade Helps Prices	Tariff Hurts Prices	Trade Hurts Helps Jobs	Trade Helps Hurts Jobs	Trade Helps Prices sans China	Trade Helps Prices sans Cheaper
Biodata									
Gender: Male	0.45 [0.50]	0.47 [0.50]	0.48 [0.50]	0.48 [0.50]	0.49 [0.50]	0.49 [0.50]	0.48 [0.50]	0.44 [0.50]	0.46 [0.50]
Gender: Female	0.55 [0.50]	0.53 [0.50]	0.52 [0.50]	0.51 [0.50]	0.51 [0.50]	0.50 [0.50]	0.52 [0.50]	0.55 [0.50]	0.53 [0.50]
Age: Average (approx.)	44.34 [16.48]	44.88 [17.10]	44.43 [16.88]	44.15 [16.48]	45.31 [16.77]	45.76 [16.75]	47.32 [16.38]	46.78 [15.91]	48.80 [15.52]
Race: White	0.69 [0.46]	0.66 [0.47]	0.67 [0.47]	0.64 [0.48]	0.68 [0.47]	0.69 [0.46]	0.70 [0.46]	0.65 [0.48]	0.64 [0.48]
Race: African-American	0.11 [0.32]	0.13 [0.34]	0.13 [0.34]	0.16 [0.37]	0.12 [0.32]	0.13 [0.34]	0.13 [0.34]	0.11 [0.31]	0.10 [0.30]
Race: Hispanic	0.11 [0.32]	0.14 [0.35]	0.13 [0.33]	0.14 [0.35]	0.13 [0.34]	0.11 [0.32]	0.10 [0.31]	0.18 [0.38]	0.17 [0.38]
Born in US?	0.93 [0.25]	0.93 [0.26]	0.93 [0.26]	0.92 [0.28]	0.91 [0.28]	0.92 [0.27]	0.93 [0.25]	0.92 [0.27]	0.90 [0.30]
Socio-Economic Characteristics									
Household Income: Average \$ (approx.)	66,541 [54,351]	64,642 [53,897]	63,792 [54,351]	64,681 [54,427]	66,636 [55,145]	65,231 [52,956]	63,136 [50,864]	64,825 [55,512]	63,651 [54,416]
Education: Average years (approx.)	12.09 [4.83]	11.62 [4.90]	11.74 [4.78]	11.74 [4.82]	11.55 [4.90]	11.66 [4.73]	11.54 [4.85]	10.68 [4.93]	10.96 [4.92]
Employment Status: Not in Labor Force	0.36 [0.48]	0.40 [0.49]	0.36 [0.48]	0.38 [0.49]	0.39 [0.49]	0.42 [0.49]	0.40 [0.49]	0.38 [0.49]	0.41 [0.49]
Employment Status: Unemployed	0.15 [0.36]	0.12 [0.32]	0.12 [0.32]	0.10 [0.30]	0.10 [0.30]	0.10 [0.30]	0.09 [0.29]	0.13 [0.33]	0.09 [0.29]
Employment Status: Employed	0.49 [0.50]	0.48 [0.50]	0.52 [0.50]	0.52 [0.50]	0.51 [0.50]	0.48 [0.50]	0.51 [0.50]	0.49 [0.50]	0.50 [0.50]
Employment Sector: Manufacturing	0.07 [0.25]	0.09 [0.29]	0.09 [0.29]	0.09 [0.28]	0.11 [0.31]	0.08 [0.27]	0.07 [0.25]	0.09 [0.28]	0.08 [0.27]
Employment Sector: Services	0.37 [0.48]	0.32 [0.47]	0.38 [0.48]	0.37 [0.48]	0.36 [0.48]	0.35 [0.48]	0.38 [0.49]	0.36 [0.48]	0.38 [0.48]
Student?	0.04 [0.19]	0.05 [0.22]	0.05 [0.21]	0.05 [0.21]	0.05 [0.22]	0.05 [0.21]	0.04 [0.20]	0.02 [0.14]	0.03 [0.17]
Loss aversion (Scale: 1 to 5)	3.08 [1.46]	3.09 [1.47]	3.23 [1.44]	3.15 [1.45]	3.10 [1.46]	3.06 [1.52]	3.02 [1.46]	3.11 [1.48]	3.10 [1.56]
Baseline Socio-Political Attributes									
Last Presidential election: Supported Dem.	0.41 [0.49]	0.41 [0.49]	0.39 [0.49]	0.42 [0.49]	0.42 [0.49]	0.39 [0.49]	0.42 [0.49]	0.42 [0.49]	0.42 [0.49]
Last Presidential election: Supported Rep.	0.36 [0.48]	0.35 [0.48]	0.36 [0.48]	0.36 [0.48]	0.37 [0.48]	0.38 [0.49]	0.36 [0.48]	0.33 [0.47]	0.39 [0.49]
Trust in government? (Scale: 1 to 5)	2.77 [1.13]	2.79 [1.13]	2.83 [1.14]	2.82 [1.12]	2.77 [1.12]	2.78 [1.11]	2.83 [1.16]	2.69 [1.15]	2.79 [1.16]
Impact of NAFTA on family (Scale: 1 to 5)	3.39 [0.91]	3.34 [0.85]	3.34 [0.94]	3.41 [0.88]	3.32 [0.89]	3.35 [0.91]	3.33 [0.86]	3.33 [0.90]	3.29 [0.95]
Children born into better life? (Scale: 1 to 5)	3.24 [1.09]	3.26 [1.11]	3.27 [1.07]	3.27 [1.08]	3.23 [1.08]	3.19 [1.10]	3.24 [1.08]	3.11 [1.14]	3.15 [1.15]
Satisfied with health of US job market?	0.34 [0.47]	0.36 [0.48]	0.34 [0.47]	0.37 [0.48]	0.34 [0.47]	0.32 [0.47]	0.33 [0.47]	0.36 [0.48]	0.32 [0.47]
Willing to pay more for US brand?	0.66 [0.48]	0.64 [0.48]	0.64 [0.48]	0.68 [0.47]	0.63 [0.48]	0.64 [0.48]	0.65 [0.48]	0.64 [0.48]	0.68 [0.47]
Inequality in US a problem? (Scale: 1 to 4)	2.92 [0.95]	2.95 [0.96]	2.97 [0.94]	2.98 [0.93]	2.98 [0.94]	2.84 [0.98]	2.93 [0.91]	3.07 [0.95]	3.01 [0.96]
News consumption patterns									
Number of days per week (approx.)	5.41 [2.26]	5.24 [2.38]	5.17 [2.45]	5.36 [2.28]	5.16 [2.40]	5.35 [2.30]	5.58 [2.16]	5.19 [2.39]	5.33 [2.36]
Main tv source: Broadcast tv	0.24 [0.43]	0.29 [0.45]	0.24 [0.43]	0.25 [0.44]	0.26 [0.44]	0.25 [0.43]	0.28 [0.45]	0.22 [0.41]	0.26 [0.44]
Main tv source: CNN, MSNBC	0.22 [0.41]	0.20 [0.40]	0.21 [0.41]	0.20 [0.40]	0.20 [0.40]	0.20 [0.40]	0.19 [0.39]	0.23 [0.42]	0.21 [0.41]
Main tv source: Fox News	0.18 [0.38]	0.17 [0.38]	0.20 [0.40]	0.16 [0.37]	0.17 [0.38]	0.17 [0.38]	0.19 [0.40]	0.15 [0.36]	0.16 [0.37]
Location Characteristics									
Share with college and above (age>=25)	0.32 [0.12]	0.31 [0.12]	0.31 [0.12]	0.31 [0.12]	0.32 [0.12]	0.30 [0.11]	0.31 [0.11]	0.32 [0.12]	0.30 [0.12]
Autor-Dorn-Hanson measure for 2000s	2.59 [2.02]	2.46 [1.91]	2.71 [2.40]	2.51 [2.18]	2.55 [2.05]	2.60 [2.32]	2.66 [1.88]	2.51 [1.79]	2.55 [2.34]
Share of manufacturing in employment	0.16 [0.11]	0.15 [0.11]	0.16 [0.11]	0.15 [0.11]	0.15 [0.11]	0.16 [0.11]	0.16 [0.12]	0.16 [0.12]	0.16 [0.12]
Urban?	0.89 [0.32]	0.88 [0.33]	0.86 [0.35]	0.87 [0.33]	0.88 [0.33]	0.89 [0.32]	0.87 [0.34]	0.89 [0.31]	0.84 [0.36]
Survey Characteristics									
Duration to complete (secs.)	887 [1,812]	871 [1,204]	952 [2,337]	1,031 [4,706]	924 [1,263]	779 [727]	831 [1,113]	854 [737]	1,003 [2,240]
Treatment duration	---	26 [78]	33 [96]	32 [165]	26 [44]	34 [46]	34 [42]	28 [55]	31 [60]
Mobile device?	0.71 [0.46]	0.71 [0.46]	0.69 [0.46]	0.70 [0.46]	0.69 [0.46]	0.64 [0.48]	0.65 [0.48]	0.77 [0.42]	0.72 [0.45]

Notes: Mean values reported for each control or treatment group, with standard deviations in brackets. For respondent age, household income, and frequency of news consumption, this is approximated by a weighted average of the midpoint values of the response option bins, using the share of respondents picking each bin as weights. For respondent years of education, an analogous weighted average is taken that assigns 6 years to "High school or less", 14 years to "Some college", 16 years to "College graduate", and 18 years to "Post graduate". The randomization-t p-value (c.f., Young 2019) for a multiple hypothesis test of the orthogonality of the above covariates with respect to the Round 2 treatment dummies is 0.019 when age and education years are included, and 0.546 when these two variables are excluded (based on 1,000 iterations, controlling for survey-week fixed effects); we exclude from the covariate set examined in this test the survey and treatment duration variables (which mechanically differ across treatments), and the male gender and out of labor force dummies (due to collinearity with other variables).

Appendix Table 1c
Treatment Balance: Survey Round 3 (2021)

TREATMENT:	Control	Trade Hurts Jobs	Trade Helps Jobs	Trade Helps Prices	Tariff Hurts Prices	Trade Hurts Helps Jobs	Trade Helps Hurts Jobs	Trade Helps Prices sans China	Trade Helps Prices sans Cheaper
Biodata									
Gender: Male	0.46 [0.50]	0.50 [0.50]	0.46 [0.50]	0.51 [0.50]	0.48 [0.50]	0.50 [0.50]	0.50 [0.50]	0.48 [0.50]	0.50 [0.50]
Gender: Female	0.54 [0.50]	0.50 [0.50]	0.53 [0.50]	0.49 [0.50]	0.52 [0.50]	0.49 [0.50]	0.50 [0.50]	0.52 [0.50]	0.50 [0.50]
Age: Average (approx.)	45.53 [17.23]	45.91 [16.49]	46.29 [16.50]	47.19 [16.97]	45.96 [17.10]	46.76 [16.15]	47.44 [16.77]	47.65 [16.57]	46.20 [16.43]
Race: White	0.61 [0.49]	0.61 [0.49]	0.62 [0.49]	0.64 [0.48]	0.64 [0.48]	0.60 [0.49]	0.62 [0.49]	0.63 [0.48]	0.63 [0.48]
Race: African-American	0.13 [0.33]	0.13 [0.34]	0.12 [0.33]	0.11 [0.31]	0.10 [0.30]	0.12 [0.33]	0.13 [0.34]	0.12 [0.33]	0.10 [0.30]
Race: Hispanic	0.16 [0.37]	0.18 [0.38]	0.18 [0.39]	0.17 [0.37]	0.17 [0.37]	0.18 [0.38]	0.16 [0.37]	0.19 [0.39]	0.20 [0.40]
Born in US?	0.90 [0.30]	0.91 [0.28]	0.91 [0.29]	0.94 [0.24]	0.92 [0.27]	0.91 [0.29]	0.89 [0.31]	0.93 [0.26]	0.92 [0.28]
Socio-Economic Characteristics									
Household Income: Average \$ (approx.)	61,560 [50,471]	61,932 [48,021]	60,963 [46,445]	66,472 [54,351]	64,456 [51,312]	59,767 [49,064]	60,991 [48,760]	58,790 [46,746]	63,182 [49,566]
Education: Average years (approx.)	11.83 [4.89]	11.57 [4.87]	11.89 [4.82]	11.52 [4.98]	11.86 [4.83]	11.72 [4.80]	11.95 [4.90]	11.57 [4.89]	11.43 [4.89]
Employment Status: Not in Labor Force	0.42 [0.49]	0.36 [0.48]	0.41 [0.49]	0.44 [0.50]	0.40 [0.49]	0.34 [0.48]	0.41 [0.49]	0.40 [0.49]	0.37 [0.48]
Employment Status: Unemployed	0.09 [0.29]	0.11 [0.32]	0.11 [0.31]	0.08 [0.28]	0.10 [0.30]	0.13 [0.33]	0.10 [0.30]	0.09 [0.29]	0.11 [0.31]
Employment Status: Employed	0.49 [0.50]	0.53 [0.50]	0.49 [0.50]	0.47 [0.50]	0.50 [0.50]	0.53 [0.50]	0.50 [0.50]	0.51 [0.50]	0.52 [0.50]
Employment Sector: Manufacturing	0.07 [0.26]	0.07 [0.26]	0.10 [0.30]	0.07 [0.26]	0.05 [0.21]	0.09 [0.28]	0.06 [0.23]	0.08 [0.27]	0.08 [0.27]
Employment Sector: Services	0.38 [0.49]	0.42 [0.49]	0.36 [0.48]	0.37 [0.48]	0.40 [0.49]	0.39 [0.49]	0.41 [0.49]	0.39 [0.49]	0.40 [0.49]
Student?	0.06 [0.24]	0.02 [0.15]	0.04 [0.21]	0.05 [0.21]	0.05 [0.22]	0.02 [0.16]	0.04 [0.18]	0.05 [0.22]	0.03 [0.17]
Loss aversion (Scale: 1 to 5)	3.14 [1.48]	3.16 [1.48]	3.17 [1.55]	3.07 [1.51]	3.08 [1.52]	2.97 [1.49]	2.93 [1.45]	3.06 [1.52]	3.08 [1.47]
Baseline Socio-Political Attributes									
Last Presidential election: Supported Dem.	0.51 [0.50]	0.53 [0.50]	0.49 [0.50]	0.48 [0.50]	0.48 [0.50]	0.48 [0.50]	0.52 [0.50]	0.50 [0.50]	0.45 [0.50]
Last Presidential election: Supported Rep.	0.30 [0.46]	0.32 [0.47]	0.32 [0.47]	0.35 [0.48]	0.32 [0.47]	0.31 [0.46]	0.31 [0.47]	0.34 [0.47]	0.36 [0.48]
Trust in government? (Scale: 1 to 5)	2.66 [1.11]	2.69 [1.16]	2.63 [1.07]	2.80 [1.16]	2.77 [1.10]	2.59 [1.10]	2.73 [1.10]	2.61 [1.11]	2.69 [1.08]
Impact of NAFTA on family (Scale: 1 to 5)	3.30 [0.88]	3.32 [0.92]	3.28 [0.90]	3.40 [0.88]	3.33 [0.85]	3.30 [0.83]	3.28 [0.87]	3.23 [0.85]	3.33 [0.85]
Children born into better life? (Scale: 1 to 5)	3.11 [1.16]	3.16 [1.17]	3.10 [1.08]	3.25 [1.19]	3.21 [1.14]	3.17 [1.14]	3.12 [1.11]	3.07 [1.17]	3.22 [1.15]
Satisfied with health of US job market?	0.37 [0.48]	0.42 [0.49]	0.37 [0.48]	0.42 [0.49]	0.41 [0.49]	0.40 [0.49]	0.39 [0.49]	0.41 [0.49]	0.37 [0.48]
Willing to pay more for US brand?	0.61 [0.49]	0.63 [0.48]	0.63 [0.48]	0.66 [0.47]	0.65 [0.48]	0.60 [0.49]	0.64 [0.48]	0.64 [0.48]	0.64 [0.48]
Inequality in US a problem? (Scale: 1 to 4)	2.94 [1.01]	2.97 [0.98]	3.00 [0.95]	3.01 [0.92]	3.03 [0.92]	3.02 [0.94]	2.93 [0.98]	2.94 [0.97]	2.93 [0.95]
News consumption patterns									
Number of days per week (approx.)	4.94 [2.45]	4.90 [2.45]	4.88 [2.49]	5.25 [2.31]	4.99 [2.47]	4.85 [2.49]	5.05 [2.45]	5.09 [2.46]	5.10 [2.32]
Main tv source: Broadcast tv	0.25 [0.43]	0.26 [0.44]	0.24 [0.43]	0.27 [0.44]	0.24 [0.43]	0.23 [0.42]	0.27 [0.44]	0.25 [0.44]	0.25 [0.44]
Main tv source: CNN, MSNBC	0.20 [0.40]	0.19 [0.39]	0.19 [0.40]	0.20 [0.40]	0.21 [0.41]	0.22 [0.42]	0.21 [0.41]	0.19 [0.39]	0.17 [0.38]
Main tv source: Fox News	0.15 [0.36]	0.16 [0.37]	0.15 [0.36]	0.14 [0.35]	0.14 [0.35]	0.15 [0.36]	0.13 [0.34]	0.13 [0.34]	0.17 [0.38]
Location Characteristics									
Share with college and above (age>=25)	0.30 [0.10]	0.30 [0.11]	0.31 [0.11]	0.30 [0.11]	0.31 [0.11]	0.30 [0.10]	0.31 [0.11]	0.30 [0.11]	0.31 [0.11]
Autor-Dorn-Hanson measure for 2000s	2.46 [1.68]	2.46 [1.60]	2.50 [1.60]	2.63 [1.98]	2.57 [1.84]	2.55 [1.84]	2.53 [1.82]	2.64 [1.75]	2.50 [1.77]
Share of manufacturing in employment	0.16 [0.11]	0.16 [0.11]	0.16 [0.11]	0.16 [0.11]	0.17 [0.12]	0.16 [0.11]	0.16 [0.11]	0.17 [0.12]	0.16 [0.10]
Urban?	0.88 [0.33]	0.88 [0.33]	0.86 [0.35]	0.85 [0.36]	0.85 [0.36]	0.86 [0.34]	0.86 [0.35]	0.85 [0.36]	0.86 [0.35]
Survey Characteristics									
Duration to complete (secs.)	881 [853]	873 [1,106]	859 [846]	901 [672]	857 [601]	956 [949]	892 [807]	847 [621]	923 [1,959]
Treatment duration	---	26 [30]	30 [47]	31 [56]	29 [79]	41 [63]	38 [97]	31 [52]	25 [32]
Mobile device?	0.60 [0.49]	0.57 [0.50]	0.62 [0.49]	0.54 [0.50]	0.57 [0.49]	0.59 [0.49]	0.57 [0.49]	0.56 [0.50]	0.57 [0.50]

Notes: Mean values reported for each control or treatment group, with standard deviations in brackets. For respondent age, household income, and frequency of news consumption, this is approximated by a weighted average of the midpoint values of the response option bins, using the share of respondents picking each bin as weights. For respondent years of education, an analogous weighted average is taken that assigns 6 years to "High school or less", 14 years to "Some college", 16 years to "College graduate", and 18 years to "Post graduate". The randomization-t p-value (c.f., Young 2019) for a multiple hypothesis test of the orthogonality of the above covariates with respect to the Round 3 treatment dummies is 0.509 (based on 1,000 iterations, controlling for survey-week fixed effects); we exclude from the covariate set examined in this test the survey and treatment duration variables (which mechanically differ across treatments), and the male gender and out of labor force dummies (due to collinearity with other variables).

Appendix Table 1d
Treatment Balance: Survey Round 4 (2022)

TREATMENT:	Control	Trade Hurts Jobs	Trade Helps Jobs	Trade Helps Prices	Tariff Hurts Prices	Trade Hurts Helps Jobs	Trade Helps Hurts Jobs
<u>Biodata</u>							
Gender: Male	0.48 [0.50]	0.46 [0.50]	0.47 [0.50]	0.49 [0.50]	0.50 [0.50]	0.49 [0.50]	0.46 [0.50]
Gender: Female	0.52 [0.50]	0.53 [0.50]	0.53 [0.50]	0.51 [0.50]	0.49 [0.50]	0.50 [0.50]	0.53 [0.50]
Age: Average (approx.)	46.02 [16.90]	46.58 [16.11]	46.88 [16.84]	47.47 [16.51]	45.66 [17.02]	46.94 [16.14]	46.04 [17.48]
Race: White	0.61 [0.49]	0.63 [0.48]	0.63 [0.48]	0.62 [0.49]	0.62 [0.49]	0.65 [0.48]	0.61 [0.49]
Race: African-American	0.12 [0.33]	0.13 [0.34]	0.11 [0.32]	0.12 [0.33]	0.11 [0.31]	0.13 [0.33]	0.14 [0.35]
Race: Hispanic	0.18 [0.38]	0.15 [0.36]	0.18 [0.39]	0.17 [0.38]	0.18 [0.39]	0.15 [0.36]	0.15 [0.36]
Born in US?	0.91 [0.29]	0.93 [0.26]	0.93 [0.25]	0.93 [0.26]	0.93 [0.26]	0.91 [0.28]	0.90 [0.29]
<u>Socio-Economic Characteristics</u>							
Household Income: Average \$ (approx.)	56,923 [44,204]	58,259 [45,365]	61,117 [47,971]	61,637 [48,177]	58,484 [44,529]	60,407 [44,629]	58,900 [45,744]
Education: Average years (approx.)	11.55 [4.81]	11.73 [4.85]	11.71 [4.95]	11.91 [4.89]	11.93 [4.84]	11.98 [4.77]	11.68 [4.88]
Employment Status: Not in Labor Force	0.38 [0.49]	0.38 [0.48]	0.41 [0.49]	0.39 [0.49]	0.41 [0.49]	0.38 [0.49]	0.40 [0.49]
Employment Status: Unemployed	0.12 [0.32]	0.11 [0.31]	0.10 [0.30]	0.09 [0.29]	0.09 [0.29]	0.08 [0.28]	0.09 [0.29]
Employment Status: Employed	0.50 [0.50]	0.52 [0.50]	0.48 [0.50]	0.52 [0.50]	0.50 [0.50]	0.53 [0.50]	0.51 [0.50]
Employment Sector: Manufacturing	0.08 [0.27]	0.05 [0.22]	0.07 [0.25]	0.06 [0.25]	0.07 [0.25]	0.05 [0.22]	0.07 [0.26]
Employment Sector: Services	0.39 [0.49]	0.42 [0.49]	0.39 [0.49]	0.41 [0.49]	0.39 [0.49]	0.43 [0.49]	0.42 [0.49]
Student?	0.02 [0.15]	0.03 [0.16]	0.03 [0.17]	0.03 [0.16]	0.04 [0.20]	0.04 [0.20]	0.04 [0.19]
Loss aversion (Scale: 1 to 5)	3.12 [1.46]	3.13 [1.53]	2.98 [1.53]	3.01 [1.51]	3.06 [1.47]	3.04 [1.48]	3.12 [1.47]
<u>Baseline Socio-Political Attributes</u>							
Last Presidential election: Supported Dem.	0.43 [0.50]	0.47 [0.50]	0.47 [0.50]	0.46 [0.50]	0.45 [0.50]	0.42 [0.49]	0.41 [0.49]
Last Presidential election: Supported Rep.	0.34 [0.48]	0.31 [0.46]	0.33 [0.47]	0.36 [0.48]	0.35 [0.48]	0.39 [0.49]	0.36 [0.48]
Trust in government? (Scale: 1 to 5)	2.54 [1.12]	2.57 [1.06]	2.62 [1.08]	2.51 [1.06]	2.54 [1.06]	2.50 [1.02]	2.53 [1.01]
Impact of NAFTA on family (Scale: 1 to 5)	3.10 [0.91]	3.23 [0.90]	3.15 [0.86]	3.09 [0.88]	3.08 [0.88]	3.13 [0.89]	3.10 [0.87]
Children born into better life? (Scale: 1 to 5)	2.92 [1.18]	3.00 [1.13]	3.08 [1.09]	3.01 [1.10]	2.96 [1.12]	3.03 [1.13]	2.99 [1.09]
Satisfied with health of US job market?	0.41 [0.49]	0.45 [0.50]	0.40 [0.49]	0.43 [0.50]	0.38 [0.48]	0.41 [0.49]	0.42 [0.49]
Willing to pay more for US brand?	0.60 [0.49]	0.62 [0.48]	0.65 [0.48]	0.59 [0.49]	0.60 [0.49]	0.60 [0.49]	0.63 [0.48]
Inequality in US a problem? (Scale: 1 to 4)	2.99 [0.93]	3.02 [0.92]	3.03 [0.95]	3.04 [0.89]	3.07 [0.95]	2.92 [0.93]	2.91 [0.95]
Inflation in US a problem? (Scale: 1 to 4)	3.40 [0.82]	3.45 [0.78]	3.41 [0.80]	3.38 [0.79]	3.47 [0.78]	3.42 [0.79]	3.43 [0.76]
<u>News consumption patterns</u>							
Number of days per week (approx.)	4.86 [2.51]	4.90 [2.52]	5.03 [2.48]	5.10 [2.47]	4.92 [2.54]	4.92 [2.51]	4.90 [2.46]
Main tv source: Broadcast tv	0.24 [0.43]	0.27 [0.44]	0.25 [0.43]	0.27 [0.45]	0.28 [0.45]	0.26 [0.44]	0.26 [0.44]
Main tv source: CNN, MSNBC	0.15 [0.36]	0.15 [0.36]	0.19 [0.40]	0.15 [0.36]	0.16 [0.37]	0.15 [0.35]	0.15 [0.36]
Main tv source: Fox News	0.16 [0.37]	0.16 [0.37]	0.15 [0.36]	0.18 [0.38]	0.15 [0.35]	0.17 [0.38]	0.15 [0.36]
<u>Location Characteristics</u>							
Share with college and above (age>=25)	0.30 [0.10]	0.30 [0.10]	0.29 [0.10]	0.31 [0.11]	0.30 [0.11]	0.30 [0.11]	0.31 [0.11]
Autor-Dorn-Hanson measure for 2000s	2.63 [2.03]	2.45 [1.72]	2.49 [1.78]	2.74 [1.89]	2.61 [2.11]	2.46 [1.79]	2.72 [2.13]
Share of manufacturing in employment	0.16 [0.11]	0.16 [0.10]	0.15 [0.10]	0.17 [0.11]	0.16 [0.11]	0.17 [0.11]	0.17 [0.11]
Urban?	0.86 [0.35]	0.85 [0.35]	0.83 [0.38]	0.86 [0.35]	0.85 [0.36]	0.85 [0.35]	0.87 [0.33]
<u>Survey Characteristics</u>							
Duration to complete (secs.)	892 [957]	862 [674]	885 [644]	938 [889]	857 [618]	836 [590]	944 [1,246]
Treatment duration	---	29 [53]	29 [49]	30 [63]	26 [27]	36 [40]	37 [56]
Mobile device?	0.57 [0.50]	0.49 [0.50]	0.43 [0.50]	0.51 [0.50]	0.45 [0.50]	0.51 [0.50]	0.51 [0.50]

Notes: Mean values reported for each control or treatment group (across Appendix Tables 1d and 1e for Round 4), with standard deviations in brackets. For respondent age, household income, and frequency of news consumption, this is approximated by a weighted average of the midpoint values of the response option bins, using the share of respondents picking each bin as weights. For respondent years of education, an analogous weighted average is taken that assigns 6 years to "High school or less", 14 years to "Some college", 16 years to "College graduate", and 18 years to "Post graduate". The randomization-t p-value (c.f., Young 2019) for a multiple hypothesis test of the orthogonality of the above covariates with respect to the Round 4 treatment dummies is 0.438 (based on 1,000 iterations, controlling for survey-week fixed effects); we exclude from the covariate set examined in this test the survey and treatment duration variables (which mechanically differ across treatments), and the male gender and out of labor force dummies (due to collinearity with other variables).

Appendix Table 1e
Treatment Balance: Survey Round 4 (2022)

TREATMENT:	Trade Hurts Jobs sans China	Trade Helps Jobs sans China	Trade Helps Prices sans China	Trade Helps Prices sans Cheaper
<u>Biodata</u>				
Gender: Male	0.48 [0.50]	0.46 [0.50]	0.48 [0.50]	0.45 [0.50]
Gender: Female	0.51 [0.50]	0.53 [0.50]	0.52 [0.50]	0.54 [0.50]
Age: Average (approx.)	47.22 [16.45]	45.77 [17.13]	46.83 [16.84]	46.04 [17.00]
Race: White	0.58 [0.49]	0.60 [0.49]	0.64 [0.48]	0.62 [0.48]
Race: African-American	0.13 [0.34]	0.12 [0.32]	0.10 [0.31]	0.10 [0.30]
Race: Hispanic	0.17 [0.37]	0.18 [0.39]	0.17 [0.37]	0.19 [0.40]
Born in US?	0.92 [0.27]	0.91 [0.29]	0.91 [0.29]	0.93 [0.25]
<u>Socio-Economic Characteristics</u>				
Household Income: Average \$ (approx.)	59,668 [48,033]	55,052 [45,223]	60,556 [45,293]	58,953 [46,291]
Education: Average years (approx.)	11.73 [4.90]	11.56 [4.87]	11.73 [4.84]	11.44 [4.95]
Employment Status: Not in Labor Force	0.38 [0.49]	0.41 [0.49]	0.40 [0.49]	0.36 [0.48]
Employment Status: Unemployed	0.12 [0.33]	0.09 [0.29]	0.09 [0.29]	0.10 [0.29]
Employment Status: Employed	0.50 [0.50]	0.50 [0.50]	0.50 [0.50]	0.54 [0.50]
Employment Sector: Manufacturing	0.09 [0.28]	0.07 [0.26]	0.07 [0.26]	0.08 [0.27]
Employment Sector: Services	0.36 [0.48]	0.38 [0.49]	0.41 [0.49]	0.42 [0.49]
Student?	0.02 [0.13]	0.04 [0.18]	0.03 [0.17]	0.03 [0.17]
Loss aversion (Scale: 1 to 5)	3.07 [1.50]	3.03 [1.47]	2.92 [1.52]	3.09 [1.55]
<u>Baseline Socio-Political Attributes</u>				
Last Presidential election: Supported Dem.	0.45 [0.50]	0.49 [0.50]	0.39 [0.49]	0.45 [0.50]
Last Presidential election: Supported Rep.	0.32 [0.47]	0.29 [0.46]	0.37 [0.48]	0.36 [0.48]
Trust in government? (Scale: 1 to 5)	2.53 [1.09]	2.57 [1.08]	2.53 [1.10]	2.55 [1.10]
Impact of NAFTA on family (Scale: 1 to 5)	3.07 [0.96]	3.12 [0.93]	3.06 [0.93]	3.10 [0.93]
Children born into better life? (Scale: 1 to 5)	2.83 [1.15]	2.97 [1.13]	2.94 [1.14]	2.83 [1.21]
Satisfied with health of US job market?	0.42 [0.49]	0.43 [0.50]	0.40 [0.49]	0.38 [0.49]
Willing to pay more for US brand?	0.59 [0.49]	0.60 [0.49]	0.63 [0.48]	0.63 [0.48]
Inequality in US a problem? (Scale: 1 to 4)	3.04 [0.94]	3.04 [0.93]	2.91 [1.00]	2.95 [0.96]
Inflation in US a problem? (Scale: 1 to 4)	3.40 [0.81]	3.40 [0.82]	3.45 [0.79]	3.41 [0.82]
<u>News consumption patterns</u>				
Number of days per week (approx.)	4.68 [2.57]	4.78 [2.56]	4.82 [2.52]	4.70 [2.54]
Main tv source: Broadcast tv	0.28 [0.45]	0.22 [0.42]	0.25 [0.43]	0.27 [0.45]
Main tv source: CNN, MSNBC	0.16 [0.36]	0.18 [0.38]	0.18 [0.38]	0.16 [0.37]
Main tv source: Fox News	0.16 [0.37]	0.17 [0.37]	0.16 [0.37]	0.16 [0.36]
<u>Location Characteristics</u>				
Share with college and above (age>=25)	0.30 [0.11]	0.29 [0.10]	0.30 [0.10]	0.30 [0.10]
Autor-Dorn-Hanson measure for 2000s	2.60 [1.89]	2.49 [1.80]	2.57 [2.51]	2.93 [2.47]
Share of manufacturing in employment	0.16 [0.11]	0.16 [0.12]	0.17 [0.11]	0.17 [0.11]
Urban?	0.83 [0.38]	0.85 [0.36]	0.87 [0.34]	0.85 [0.36]
<u>Survey Characteristics</u>				
Duration to complete (secs.)	931 [1,177]	960 [1,132]	862 [657]	883 [1,047]
Treatment duration	34 [126]	31 [90]	29 [36]	25 [34]
Mobile device?	0.66 [0.48]	0.65 [0.48]	0.52 [0.50]	0.54 [0.50]

Notes: See notes to Table 1d.

Appendix Table 2
Effect of Information Treatments on Preferences Towards Trade Policy: Full Results
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Dependent Variable:	(1) First principal component OLS	(2) First principal component OLS	(3) Did information affect views? Ordered logit	(4) Impact of trade for most Americans? Ordered logit
<u>Treatment dummies:</u> (Omitted: Control group)				
Trade Hurts Jobs	0.211*** [0.042]	0.242*** [0.043]	0.048*** [0.015]	-0.248*** [0.016]
Trade Helps Jobs	0.049 [0.047]	0.081* [0.044]	0.030* [0.016]	-0.025* [0.015]
Trade Helps Prices	0.099** [0.040]	0.109*** [0.042]	0.028* [0.015]	-0.058*** [0.015]
Tariff Hurts Prices	0.075* [0.042]	0.099** [0.042]	0.046*** [0.016]	-0.164*** [0.016]
Most Pref., Randomization Order		-0.019*** [0.007]		
<u>Individual Controls:</u>				
Gender (Omitted: Male)				
Female		-0.044 [0.029]	-0.040*** [0.009]	-0.053*** [0.009]
Other		-0.200 [0.211]	0.075 [0.090]	0.028 [0.071]
Age (Omitted: 18-24)				
25-34		0.135*** [0.042]	0.008 [0.019]	-0.043*** [0.015]
35-44		0.330*** [0.047]	0.012 [0.019]	-0.081*** [0.017]
45-54		0.500*** [0.054]	-0.090*** [0.018]	-0.171*** [0.019]
55-64		0.621*** [0.060]	-0.116*** [0.020]	-0.171*** [0.020]
Above 65		0.696*** [0.064]	-0.108*** [0.021]	-0.155*** [0.021]
Race (Omitted: White)				
African-American		0.057 [0.047]	0.016 [0.018]	-0.022 [0.015]
Hispanic, Latino or Spanish Origin		0.023 [0.043]	-0.007 [0.017]	0.002 [0.013]
Asian		-0.087 [0.078]	-0.008 [0.022]	-0.028 [0.025]
Other		0.071 [0.081]	0.031 [0.029]	-0.010 [0.031]
Education: College and above?		-0.022 [0.035]	-0.005 [0.011]	0.037*** [0.011]
Household Income (Omitted: \$0-\$49,999)				
\$50,000-\$99,999		0.081** [0.033]	-0.005 [0.011]	0.003 [0.011]
\$100,000-\$150,000		0.114** [0.053]	0.011 [0.017]	0.054*** [0.020]
\$150,000-\$200,000		0.134* [0.077]	0.093** [0.037]	0.118*** [0.023]
>\$200,000		0.254*** [0.088]	0.045 [0.037]	0.182*** [0.021]
Unsure		-0.164*** [0.058]	-0.033 [0.021]	-0.035 [0.022]
Employment Status (Omitted: Not in labor force)				
Not employed, looking for work		-0.013 [0.047]	0.039** [0.016]	0.002 [0.018]
Student		0.092 [0.073]	0.065* [0.035]	0.006 [0.025]
Employed, in Agriculture		0.301*** [0.084]	0.258*** [0.030]	0.163*** [0.025]
Employed, in Mining		0.354*** [0.093]	0.238*** [0.042]	0.137*** [0.028]
Employed, in Manufacturing		0.124** [0.055]	0.121*** [0.023]	0.060*** [0.022]
Employed, in Services		0.042 [0.038]	0.048*** [0.012]	0.028** [0.013]
Responded on Mobile Device?		0.170*** [0.031]	0.040*** [0.010]	0.010 [0.011]
In most recent presidential election (Omitted: Neither)				
Supported Democrat		-0.141*** [0.035]	0.093*** [0.013]	0.089*** [0.012]
Supported Republican		0.625*** [0.040]	0.084*** [0.013]	-0.002 [0.013]
Frequency following news (Omitted: < once a week)				
1-2 times a week		0.159*** [0.056]	0.056*** [0.016]	0.055*** [0.019]
3-6 times a week		0.169*** [0.050]	0.106*** [0.015]	0.083*** [0.019]
Daily		0.201*** [0.047]	0.105*** [0.014]	0.119*** [0.017]
Main News Source (Omitted: Broadcast TV news)				
CNN/BBC		-0.121*** [0.039]	0.007 [0.017]	0.037** [0.014]
Fox News		0.246*** [0.045]	-0.066*** [0.015]	-0.023 [0.016]
Local TV news station		0.010 [0.039]	-0.089*** [0.013]	-0.067*** [0.013]
News/Evening News/Other program source		-0.144*** [0.041]	-0.118*** [0.014]	-0.054*** [0.016]
Region of Birth (Omitted: New England)				
Midwest		0.136* [0.073]	0.031 [0.026]	0.013 [0.024]
Great Lakes		0.168** [0.069]	0.006 [0.023]	0.005 [0.022]
Plains		0.110 [0.078]	-0.021 [0.024]	-0.000 [0.027]
Southeast		0.096 [0.067]	0.018 [0.022]	0.017 [0.021]
Southwest		0.073 [0.077]	0.031 [0.026]	0.042* [0.023]

Rocky Mountain		-0.131 [0.103]	0.017 [0.030]	0.033 [0.035]
Far West		0.061 [0.067]	0.031 [0.026]	0.021 [0.022]
Others or Missing		-0.116 [0.185]	0.171** [0.077]	-0.056 [0.092]
Not born in US		-0.049 [0.083]	0.031 [0.026]	0.037 [0.027]
County Controls:				
Share with college education (age>=25)		-0.279 [0.172]	0.102 [0.079]	0.254*** [0.069]
Autor-Dorn-Hanson measure for 2000s		-0.003 [0.007]	0.002 [0.002]	-0.001 [0.003]
Share of manufacturing in employment		0.270* [0.158]	-0.055 [0.050]	0.068 [0.052]
Urban?		-0.019 [0.047]	-0.011 [0.016]	-0.014 [0.016]
County characteristics filled?		0.121** [0.059]	0.115*** [0.034]	0.086*** [0.030]
Round-Week Dummies: (Omitted: Rd 2, Wk 1)				
Round 2, Week 2		-0.494* [0.293]	-0.313*** [0.113]	-0.143** [0.065]
Round 2, Week 3		-0.628** [0.307]	-0.264** [0.113]	-0.090 [0.069]
Round 2, Week 4		-0.493* [0.284]	-0.283** [0.110]	-0.150** [0.064]
Round 2, Week 5		-0.605** [0.300]	-0.286** [0.117]	-0.108 [0.075]
Round 3, Week 1		-0.542 [0.387]	-0.347** [0.142]	-0.072 [0.125]
Round 3, Week 2		-0.519* [0.298]	-0.286** [0.113]	-0.118* [0.065]
Round 3, Week 3		-0.478 [0.294]	-0.278** [0.113]	-0.135** [0.065]
Round 3, Week 4		-0.551* [0.311]	-0.256* [0.131]	-0.206** [0.086]
Round 3, Week 5		-0.500 [0.387]	-0.246* [0.133]	-0.239** [0.114]
Round 4, Week 1		-0.207 [0.376]	-0.177 [0.135]	-0.195** [0.098]
Round 4, Week 2		-0.422 [0.296]	-0.281** [0.115]	-0.171*** [0.066]
Round 4, Week 3		-0.468 [0.297]	-0.311*** [0.116]	-0.152** [0.066]
Round 4, Week 4		-0.352 [0.295]	-0.272** [0.118]	-0.223*** [0.066]
Round 4, Week 5		-0.288 [0.307]	-0.326*** [0.120]	-0.156** [0.070]
Constant Term	-0.119*** [0.028]	-0.468 [0.305]	---	---
Observations	9,275	9,275	9,275	9,275
(Pseudo) R-squared	0.003	0.153	0.0488	0.0569

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the "Trade Hurts Jobs", "Trade Helps Jobs", "Trade Helps Prices", and "Tariff Hurts Prices" treatments. The dependent variable in Columns 1-2 is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade; that in Column 3 is a categorical variable for degree of agreement with the statement that the information received affected one's views on trade policy (1="Strongly disagree", 5="Strongly agree"); while that in Column 4 is a categorical variable asked post-treatment on views on the impact that trade has had for most Americans (1="Extremely bad", 5="Extremely good"). Columns 1-2 report OLS estimates; while Columns 3-4 report marginal effects from ordered logit regressions, on the predicted probability that either the fourth or fifth highest ordered category is selected as the response. All marginal effects are evaluated setting the initial values of the treatment dummies to zero, while setting all other right-hand side controls at their in-sample mean values. Column 1 reports a basic specification without additional controls; while Columns 2-4 report the full set of coefficients from the Table 4, Columns 5-7 specifications respectively. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 3
Robustness: Alternative Samples and Constructions of the Dependent Variable

Trade Policy Questions:	(1) First principal component	(2) First principal component	(3) First principal component	(4) First principal component	(5) Unweighted average	(6) Dummy: ≥3 protectionist policies	(7) Factor Analysis, first factor
Survey Rounds:	2	3	4	1,2,3,4	2,3,4	2,3,4	2,3,4
	OLS	OLS	OLS	OLS	OLS	OLS	OLS
<u>Treatment dummies:</u>							
Trade Hurts Jobs	0.176*** [0.061]	0.342*** [0.083]	0.256*** [0.082]	0.242*** [0.043]	0.050*** [0.009]	0.070*** [0.016]	0.133*** [0.023]
Trade Helps Jobs	0.045 [0.063]	0.050 [0.083]	0.160* [0.084]	0.081* [0.044]	0.016* [0.009]	0.020 [0.016]	0.044* [0.024]
Trade Helps Prices	0.060 [0.061]	0.123 [0.089]	0.171** [0.081]	0.109*** [0.042]	0.021** [0.009]	0.021 [0.016]	0.061*** [0.023]
Tariff Hurts Prices	0.096 [0.066]	0.072 [0.081]	0.123 [0.087]	0.099** [0.042]	0.020** [0.009]	0.024 [0.015]	0.055** [0.023]
Most Pref., Randomization Order	-0.016** [0.008]	-0.021* [0.012]	-0.021** [0.009]	-0.019*** [0.006]	-0.004*** [0.001]	-0.007*** [0.002]	-0.010*** [0.003]
Last Pres. Election: Supported Democrat	-0.165*** [0.052]	-0.148* [0.076]	-0.101 [0.062]	-0.141*** [0.035]	-0.040*** [0.007]	-0.045*** [0.013]	-0.066*** [0.019]
Last Pres. Election: Supported Republican	0.606*** [0.063]	0.615*** [0.085]	0.644*** [0.069]	0.625*** [0.040]	0.125*** [0.008]	0.186*** [0.014]	0.340*** [0.021]
Individual, county, week controls?	Y	Y	Y	Y	Y	Y	Y
Observations	4,059	2,257	2,959	9,275	9,275	9,275	9,275
(Pseudo) R-squared	0.165	0.168	0.163	0.153	0.151	0.114	0.152
Std dev. of dep variable	1.342	1.379	1.403	1.371	0.286	0.473	0.743

Notes: The sample in each Column is from the respective survey rounds described in the column headings; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the "Trade Hurts Jobs", "Trade Helps Jobs", "Trade Helps Prices", and "Tariff Hurts Prices" treatments. The dependent variable in Columns 1-3 is the first principal component measure (as in Table 4, Column 6); that in Column 4 constructs the first principal component using the expanded sample that includes Round 1 (2018-2019); that in Column 5 is an unweighted average of the five policy variables in Table 4, Columns 1-5; that in Column 6 is an indicator variable equal to 1 if the responses on at least three of these five policy questions favored more protectionism; and that in Column 7 is the first factor from a factor analysis of these five policy variables constructed with two factors; each of these measures is constructed to be increasing in preferences for more limits on trade by taking one minus the "Support More FTAs" variable. The controls included (but not reported) are as listed in the Table 3 footnotes. All columns report OLS regressions; the bottom row reports the in-sample standard deviation of the dependent variable. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 4
Robustness: Exploring the "Jobs" and "Prices" Treatments Simultaneously
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Trade Policy Questions:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	More limits on imports	US tariff rate increase	Support higher tariff	Support more FTAs	Most Pref.: More limits on Imports	First principal component	Did information affect views?	Impact of trade for most Americans?	Confidence in answer to (8)
	Logit	Logit	Logit	Logit	Logit	OLS	Ordered logit	Ordered logit	Ordered logit
Treatment dummies:									
Trade Hurts Jobs	0.090*** [0.016]	0.072*** [0.016]	0.036** [0.017]	-0.038** [0.018]	0.033** [0.015]	0.243*** [0.043]	0.048*** [0.015]	-0.247*** [0.016]	-0.022 [0.016]
Trade Helps Jobs	0.022 [0.018]	0.023 [0.015]	0.026 [0.018]	-0.006 [0.019]	0.007 [0.015]	0.079* [0.044]	0.031* [0.016]	-0.024 [0.015]	-0.018 [0.016]
Trade Helps Prices	0.057*** [0.017]	0.029** [0.014]	-0.005 [0.017]	-0.002 [0.017]	0.030** [0.015]	0.109*** [0.042]	0.029* [0.015]	-0.059*** [0.016]	-0.022 [0.015]
Tariff Hurts Prices	0.039** [0.017]	0.022 [0.015]	0.018 [0.017]	-0.005 [0.017]	0.023 [0.016]	0.100** [0.043]	0.047*** [0.016]	-0.164*** [0.016]	-0.029* [0.015]
Trade Hurts Helps Jobs	0.045** [0.019]	0.031** [0.016]	0.034* [0.019]	-0.037** [0.019]	0.049*** [0.016]	0.169*** [0.048]	0.031** [0.016]	-0.092*** [0.016]	-0.031** [0.016]
Trade Helps Hurts Jobs	0.083*** [0.018]	0.054*** [0.017]	0.026 [0.020]	-0.032* [0.019]	0.025 [0.016]	0.199*** [0.045]	0.039** [0.016]	-0.205*** [0.016]	-0.029 [0.018]
Trade Hurts Jobs sans China	0.053* [0.028]	0.080*** [0.027]	-0.007 [0.030]	-0.025 [0.027]	0.002 [0.023]	0.153** [0.070]	0.057** [0.025]	-0.203*** [0.026]	-0.034 [0.025]
Trade Helps Jobs sans China	0.055** [0.028]	0.062** [0.026]	0.015 [0.032]	0.023 [0.028]	-0.005 [0.023]	0.123 [0.076]	0.020 [0.025]	-0.020 [0.022]	0.004 [0.026]
Trade Helps Prices sans China	0.043** [0.020]	0.040*** [0.016]	-0.009 [0.019]	-0.020 [0.018]	0.019 [0.017]	0.102** [0.047]	0.006 [0.016]	-0.047*** [0.017]	-0.014 [0.016]
Trade Helps Prices sans Cheaper	0.060*** [0.020]	0.044** [0.017]	0.017 [0.019]	-0.012 [0.019]	0.020 [0.017]	0.140*** [0.048]	0.017 [0.017]	-0.055*** [0.017]	-0.007 [0.016]
Most Pref., Randomization Order					-0.010*** [0.001]	-0.018*** [0.004]			
Last Pres. Election: Supported Democrat	0.011 [0.011]	0.024*** [0.008]	-0.040*** [0.011]	0.124*** [0.010]	-0.041*** [0.009]	-0.112*** [0.027]	0.097*** [0.009]	0.103*** [0.009]	0.065*** [0.010]
Last Pres. Election: Supported Republican	0.190*** [0.012]	0.126*** [0.011]	0.141*** [0.011]	-0.032*** [0.012]	0.145*** [0.011]	0.631*** [0.031]	0.082*** [0.010]	0.010 [0.011]	0.070*** [0.010]
Individual, county, week controls?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,102	16,102	16,102	16,102	16,102	16,102	16,072	16,072	16,072
(Pseudo) R-squared	0.0694	0.0772	0.0435	0.0677	0.0752	0.146	0.0454	0.0539	0.0316

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; including respondents in the "Control" and all treatment groups. The dependent variable in Columns 1-4 is an indicator equal to 1 if the respondent indicated support for the policy in a directly-posed question; that in Column 5 is an indicator equal to 1 if the respondent identified "More limits on imports" among his/her three "Most preferred" out of the list of eight policies; that in Column 6 is the first principal component constructed to be increasing in preferences for more limits on trade; that in Column 7 is a categorical variable for degree of agreement with the statement that the information received affected one's views on trade policy (1="Strongly disagree", 5="Strongly agree"); that in Column 8 is a categorical variable asked post-treatment on views on the impact that trade has had for most Americans (1="Extremely bad", 5="Extremely good"); while that in Column 9 is an ordered categorical variable asking respondents how confident they are in their assessment on the impact trade has had for most Americans (1="Not at all confident", 5="Extremely confident"). The controls included (but not reported) are as listed in the Table 3 footnotes. Columns 1-5 report marginal effects from logit regressions; while Columns 7-9 report marginal effects from ordered logit regressions, on the predicted probability that either the fourth or fifth highest ordered category is selected as the response. All marginal effects are evaluated setting the initial values of the treatment dummies to zero, while setting all other right-hand side controls at their in-sample mean values. Column 6 reports an OLS regression. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 5
Summary Statistics: End-of-Survey Recollection of Treatment Information

SURVEY:	Round 2, 2020 (N=6,009)	Round 3, 2021 (N=4,058)	Round 4, 2022 (N=6,035)
Share of respondents who said information was about jobs	0.34 [0.47]	0.36 [0.48]	0.35 [0.48]
Share of respondents who said information was about prices	0.52 [0.50]	0.49 [0.50]	0.50 [0.50]
Share of respondents who said no information received	0.14 [0.35]	0.14 [0.35]	0.14 [0.35]
Correctly identified nature of information treatment	0.47 [0.50]	0.52 [0.50]	0.47 [0.50]
Conditional on receiving a treatment about jobs, correctly identified as such	0.42 [0.49]	0.49 [0.50]	0.46 [0.50]
Conditional on receiving a treatment about prices, correctly identified as such	0.59 [0.49]	0.63 [0.48]	0.65 [0.48]
Conditional on receiving no information treatment, correctly identified as such	0.19 [0.40]	0.25 [0.43]	0.22 [0.42]

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples.

Appendix Table 6
Robustness: Controlling for Covid Mobility and Black Lives Matter Events

Dependent variable: Sample:	(1) Rds 2,3,4 OLS	(2) Rds 2,3,4 OLS	(3) Rds 2,3,4 OLS
	First principal component, Preference for More Limits on Trade		
Indicator: Below Median Safegraph Mobility	0.027 [0.047]	--	0.028 [0.047]
Indicator: BLM Events	--	0.108 [0.067]	0.098 [0.070]
Trade Hurts Jobs	0.236*** [0.043]	0.244*** [0.043]	0.238*** [0.043]
Trade Helps Jobs	0.079* [0.044]	0.082* [0.044]	0.080* [0.044]
Trade Helps Prices	0.100** [0.042]	0.110*** [0.042]	0.101** [0.043]
Tariff Hurts Prices	0.090** [0.043]	0.100** [0.043]	0.090** [0.043]
Most Pref., Randomization Order	-0.019*** [0.006]	-0.019*** [0.006]	-0.019*** [0.006]
Last Pres. Election: Supported Democrat	-0.149*** [0.036]	-0.142*** [0.035]	-0.150*** [0.036]
Last Pres. Election: Supported Republican	0.620*** [0.040]	0.623*** [0.040]	0.619*** [0.040]
Individual, county, week controls?	Y	Y	Y
Observations	9,090	9,275	9,090
R-squared	0.155	0.153	0.155

Notes: Based on the pooled Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the "Trade Hurts Jobs", "Trade Helps Jobs", "Trade Helps Prices", and "Tariff Hurts Prices" treatments. The dependent variable is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade. The controls included (but not reported) are as listed in the Table 3 footnotes. All columns report OLS regressions. The "Below Median Safegraph Mobility" indicator is equal to 1 if the survey response was recorded in a county-week that had a lower than median number of visits to key locations of interest when compared across the Round 2 sample (as a proxy for the severity of covid-related mobility restrictions); the indicator is set to 0 in Rounds 3 and 4. The "BLM events" indicator is equal to 1 if the survey response was recorded in Round 2 from a county-week that experienced at least one Black Lives Matter event; the indicator is set to 0 in Rounds 3 and 4. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 7
Robustness: Role of Attention Paid as Captured by Treatment Duration
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Dependent variable:	(1)	(2)	(3)
Treatment duration:	Below median	Above median	Top quintile
Panel A: Recall incorrect			
Trade Hurts Jobs	0.063 [0.059]	0.225*** [0.072]	0.496*** [0.116]
Trade Helps Jobs	0.078 [0.059]	-0.045 [0.070]	-0.087 [0.125]
Trade Helps Prices	0.114* [0.061]	0.126 [0.093]	-0.003 [0.148]
Tariff Hurts Prices	0.150** [0.062]	0.010 [0.087]	0.039 [0.120]
Observations	4,232	3,576	2,722
R-squared	0.148	0.159	0.165
Panel B: Recall correct			
Trade Hurts Jobs	0.346*** [0.074]	0.431*** [0.079]	0.488*** [0.111]
Trade Helps Jobs	0.166** [0.071]	0.135* [0.075]	0.138 [0.114]
Trade Helps Prices	0.149** [0.068]	0.080 [0.059]	0.081 [0.090]
Tariff Hurts Prices	0.155*** [0.059]	0.081 [0.067]	0.009 [0.099]
Observations	3,767	4,417	3,160
R-squared	0.152	0.181	0.159
Individual, county, week, rand. order controls?	Y	Y	Y

Notes: Based on the pooled Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the "Trade Hurts Jobs", "Trade Helps Jobs", "Trade Helps Prices", and "Tariff Hurts Prices" treatments. Columns 1-3 limit the treatment group observations to those who respectively spent a duration on the treatment screen that was: (i) below median; (ii) above median; and (iii) in the longest (top) quintile, within each treatment-by-survey-round; Panels A and B further limit these treatment group observations to those with incorrect (respectively, correct) recall of the subject matter of the treatment narrative they received. The dependent variable is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade. The controls included (but not reported) are as listed in the Table 3 footnotes. All columns report OLS regressions. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 8
Exploring Mechanisms: Economic Self Interest
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022; Above-Median Treatment Duration)

Dependent variable:	First principal component, Preference for More Limits on Trade					
Respondent variable (Economic self-interest, z-scored):	Employed in Manuf.	ADH 2000s China Shock Exposure	Education: Less than College	Unemployed	Household inc. <\$50,000	Nafta: Bad impact on family
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Hurts Jobs	0.329*** [0.057]	0.331*** [0.057]	0.331*** [0.057]	0.330*** [0.057]	0.331*** [0.057]	0.328*** [0.057]
Trade Helps Jobs	0.052 [0.057]	0.052 [0.057]	0.052 [0.057]	0.051 [0.057]	0.051 [0.056]	0.055 [0.056]
Trade Helps Prices	0.090* [0.053]	0.091* [0.053]	0.091* [0.053]	0.091* [0.053]	0.091* [0.053]	0.093* [0.053]
Tariff Hurts Prices	0.057 [0.058]	0.057 [0.058]	0.057 [0.058]	0.055 [0.058]	0.057 [0.058]	0.058 [0.058]
Respondent variable	0.025 [0.027]	-0.023 [0.024]	0.001 [0.028]	-0.013 [0.026]	0.073 [0.048]	0.037 [0.027]
Trade Hurts Jobs × Respondent variable	-0.022 [0.055]	0.031 [0.053]	0.059 [0.053]	0.029 [0.052]	0.046 [0.056]	0.030 [0.057]
Trade Helps Jobs × Respondent variable	0.041 [0.048]	0.043 [0.052]	0.022 [0.054]	-0.023 [0.045]	0.093* [0.053]	0.090* [0.049]
Trade Helps Prices × Respondent variable	0.018 [0.047]	-0.013 [0.044]	-0.078 [0.053]	0.004 [0.056]	-0.000 [0.053]	0.036 [0.053]
Tariff Hurts Prices × Respondent variable	0.007 [0.049]	-0.003 [0.045]	0.035 [0.060]	-0.036 [0.054]	0.028 [0.055]	0.057 [0.058]
Individual, county, week, randomization order controls?	Y	Y	Y	Y	Y	Y
Observations	5,754	5,754	5,754	5,754	5,754	5,754
R-squared	0.172	0.172	0.173	0.172	0.173	0.175

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the "Trade Hurts Jobs", "Trade Helps Jobs", "Trade Helps Prices", and "Tariff Hurts Prices" treatments. For these latter four treatment groups, the sample is restricted to respondents who spent an above-median duration on the treatment screen. The dependent variable is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade. The controls included (but not reported) are as listed in the Table 3 footnotes; all columns also control for Democrat and Republican dummies for the candidate supported in the most recent presidential election, as well as the randomization order in which "More Limits on Imports" appeared in the Most Preferred policy question. All columns are OLS regressions, in which the respective respondent variable (expressed as a z-score) is interacted with each of the treatment group dummies. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 9
Exploring Mechanisms: Sociotropic Concerns
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022; Above-Median Treatment Duration)

Dependent variable:	First principal component, Preference for More Limits on Trade					
Respondent variable (Sociotropic concerns, z-scored):	Inequality in the US a problem?	Inflation in the US a problem?	Trust in Government	Willing to pay more for a US brand	Dissatisfied with US job market?	Disagree children will have a better life
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Hurts Jobs	0.344*** [0.056]	0.309*** [0.113]	0.330*** [0.057]	0.312*** [0.054]	0.331*** [0.057]	0.332*** [0.057]
Trade Helps Jobs	0.067 [0.057]	0.165 [0.112]	0.052 [0.057]	0.025 [0.054]	0.062 [0.057]	0.058 [0.057]
Trade Helps Prices	0.103* [0.053]	0.177 [0.108]	0.089* [0.053]	0.070 [0.053]	0.092* [0.053]	0.094* [0.053]
Tariff Hurts Prices	0.078 [0.058]	0.114 [0.117]	0.058 [0.058]	0.039 [0.054]	0.059 [0.057]	0.061 [0.058]
Respondent variable	-0.126*** [0.028]	0.066* [0.035]	0.050** [0.025]	0.317*** [0.025]	-0.062* [0.032]	-0.056** [0.025]
Trade Hurts Jobs × Respondent variable	-0.026 [0.053]	0.061 [0.109]	-0.066 [0.056]	0.039 [0.052]	0.074 [0.055]	0.077 [0.057]
Trade Helps Jobs × Respondent variable	-0.042 [0.062]	0.081 [0.105]	-0.046 [0.052]	0.032 [0.050]	-0.067 [0.053]	0.116** [0.057]
Trade Helps Prices × Respondent variable	-0.065 [0.055]	-0.070 [0.095]	0.035 [0.052]	0.058 [0.047]	-0.013 [0.050]	0.019 [0.052]
Tariff Hurts Prices × Respondent variable	-0.001 [0.053]	0.084 [0.118]	-0.048 [0.051]	0.090** [0.046]	0.051 [0.060]	-0.012 [0.052]
Individual, county, week, randomization order controls?	Y	Y	Y	Y	Y	Y
Observations	5,754	2,024	5,754	5,754	5,754	5,754
R-squared	0.181	0.180	0.173	0.226	0.175	0.174

Notes: See notes to Appendix Table 8.

Appendix Table 10
Exploring Mechanisms: Behavioral, Political Identity
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022; Above-Median Treatment Duration)

Dependent variable:	First principal component, Preference for More Limits on Trade		
Respondent variable (z-scored):	<u>Behavioral</u>	<u>Identity Politics</u>	
	Loss Aversion: No Fees vs. Discount	Supported Republican in last Pres. Election	Supported Democrat in last Pres. Election
	(1)	(2)	(3)
Trade Hurts Jobs	0.332*** [0.057]	0.332*** [0.057]	0.331*** [0.056]
Trade Helps Jobs	0.054 [0.057]	0.051 [0.057]	0.052 [0.057]
Trade Helps Prices	0.094* [0.053]	0.090* [0.053]	0.091* [0.054]
Tariff Hurts Prices	0.061 [0.058]	0.057 [0.057]	0.059 [0.058]
Respondent variable	0.024 [0.034]	0.274*** [0.033]	-0.011 [0.033]
Trade Hurts Jobs × Respondent variable	0.007 [0.061]	0.031 [0.056]	-0.121** [0.052]
Trade Helps Jobs × Respondent variable	0.036 [0.062]	0.123** [0.060]	-0.113** [0.053]
Trade Helps Prices × Respondent variable	0.103* [0.054]	0.086 [0.056]	-0.119** [0.056]
Tariff Hurts Prices × Respondent variable	0.023 [0.054]	0.119** [0.053]	-0.153*** [0.052]
Individual, county, week, randomization order controls?	Y	Y	Y
Observations	5,754	5,754	5,754
R-squared	0.174	0.174	0.174

Notes: See notes to Appendix Table 8.

Appendix Table 11
Reasons for "More Limits on Imports": The importance of "Jobs" and "China"
(Pooled: Round 3, 2021; Round 4, 2022)

Dependent variable: (5=Strongly agree, 1=Strongly disagree)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Agreement Score: Reason for "More Limits on Imports" as a Most Preferred Policy									
	OLS									
	Treatments in sample:	All	Control	Trade Hurts Jobs	Trade Hurts Jobs sans China	Trade Helps Jobs	Trade Helps Jobs sans China	Trade Helps Prices	Trade Helps Prices sans China	Tariff Hurts Prices
Reasons:										
Quality Concerns	0.182*** [0.024]	---	-0.113 [0.072]	-0.011 [0.085]	0.169** [0.072]	0.009 [0.076]	0.452*** [0.072]	0.203** [0.079]	0.338*** [0.098]	0.235*** [0.039]
National Security	0.005 [0.026]	-0.129* [0.067]	-0.375*** [0.071]	-0.092 [0.084]	0.058 [0.076]	-0.224** [0.088]	0.118 [0.079]	0.035 [0.092]	0.221** [0.094]	0.066 [0.045]
Compete with Jobs	0.498*** [0.024]	0.308*** [0.058]	0.250*** [0.061]	0.327*** [0.073]	0.442*** [0.078]	0.297*** [0.079]	0.763*** [0.072]	0.598*** [0.076]	0.669*** [0.089]	0.526*** [0.046]
Concerns about imports from China	0.551*** [0.024]	0.415*** [0.064]	0.194*** [0.068]	0.181** [0.075]	0.662*** [0.072]	0.316*** [0.099]	0.748*** [0.074]	0.586*** [0.081]	0.845*** [0.094]	0.599*** [0.043]
Other reasons	0.222*** [0.024]	0.059 [0.067]	-0.019 [0.066]	0.049 [0.084]	0.190*** [0.072]	-0.025 [0.085]	0.599*** [0.069]	0.316*** [0.083]	0.429*** [0.082]	0.191*** [0.043]
Response Randomization Order	0.024*** [0.004]	0.056*** [0.015]	0.002 [0.011]	0.007 [0.015]	0.029** [0.013]	0.029** [0.015]	0.048*** [0.013]	0.000 [0.013]	0.027** [0.014]	0.021*** [0.007]
Jobs vs Quality, p-value	[0.000]	---	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Jobs vs Nat. Security, p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Jobs vs Other Concerns, p-value	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.004]	[0.000]	[0.002]	[0.000]
China vs Quality, p-value	[0.000]	---	[0.000]	[0.013]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
China vs Nat. Security, p-value	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
China vs Other Concerns, p-value	[0.000]	[0.000]	[0.001]	[0.053]	[0.000]	[0.000]	[0.008]	[0.000]	[0.000]	[0.000]
Individual fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,759	1,485	1,584	1,098	1,410	1,026	1,500	1,536	1,470	4,650
Number of respondents	2,676	297	264	183	235	171	250	256	245	775
R-squared	0.518	0.576	0.514	0.582	0.512	0.484	0.529	0.490	0.471	0.531

Notes: The regression sample comprises respondents in Round 3 (2021) and Round 4 (2022) who selected "More limits on imports" as a top three "Most preferred" policy out of the list of eight policies, specifically: in Column 1, pooled across the Control and all treatment groups; in Column 2, the Control group only; in Columns 3-9, the treatment groups listed in the respective column headings; and in Column 10, pooled across the remaining "Trade Hurts Helps Jobs", "Trade Helps Hurts Jobs", and "Trade Helps Prices sans Cheaper" treatment groups. The dependent variable in each column is the agreement score (on a scale of 1-5) with a given reason for selecting "More limits on imports". The omitted Reason category is "persuaded/not persuaded", except in Column 2 where "Quality concerns" is omitted ("persuaded/not persuaded" was not presented to the Control group as a response option). All columns control for individual fixed effects, as well as the reason randomization order. All regressions are run using OLS. The p-values reported are for tests of equality when comparing the "Compete with Jobs" and "Concerns about imports from China" coefficients against that estimated for the other listed reasons. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 12
Analysis of Text Responses: Occurrence of "China" and "Jobs"
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Dependent variable:	(1) Text response: Listed only China to limit imports from	(2) Text response: Listed only China to limit imports from	(3) Text response: China appears in reasons for more limits on imports	(4) Text response: China appears in reasons for more limits on imports	(5) Text response: Jobs appears in reasons for more limits on imports	(6) Text response: Jobs appears in reasons for more limits on imports
Treatments in sample:	Logit Three pairs	Logit All available	Logit Three pairs	Logit All available	Logit Three pairs	Logit All available
Treatment with China	0.008 [0.023]	-0.005 [0.015]	-0.005 [0.054]	-0.006 [0.024]		
Treatment sans China	0.023 [0.023]	0.008 [0.019]	0.027 [0.048]	0.018 [0.027]		
Treatment with Jobs					0.036 [0.053]	0.037 [0.030]
Treatment with Prices					0.016 [0.059]	0.014 [0.035]
Test for equality, p-value:	[0.496]	[0.518]	[0.260]	[0.400]	[0.569]	[0.532]
Individual, county, round controls?	Y	Y	Y	Y	Y	Y
Observations	814	1,323	559	965	644	1,034
(Pseudo) R-squared	0.217	0.200	0.136	0.103	0.112	0.087

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; the omitted category in each Column is the "Control" group who received no information treatment. The odd-numbered Columns include the "Trade Hurts Jobs", "Trade Helps Jobs", and "Trade Helps Prices" treatment groups, and their "sans China" counterparts, while the even-numbered Columns include all treatment groups; only observations that gave meaningful text responses are included. The dependent variable in Columns 1-2 is an indicator variable for whether "China" was listed as a country on which the respondent supported placing more limits on imports; that in Columns 3-4 (respectively, Columns 5-6) is an indicator variable for whether "China" (respectively, "job"/"worker") appeared in the text response on other reasons for listing "More limits on imports" as a "Most Preferred" policy. The controls included (but not reported) are as listed in the Table 3 footnotes, except that round-group dummies are used in lieu of round-week dummies; we also include Democrat and Republican dummies for the candidate supported in the last presidential election. All columns report average marginal effects from logit regressions. The p-value reported in each column is for a test of equality of the coefficients for the pair of treatments. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Appendix Table 13
Baseline versus "sans China" treatments
(Pooled: Round 2, 2020; Round 3, 2021; Round 4, 2022)

Trade Policy Questions:	(1) First principal component OLS	(2) Did information affect views? Ordered logit	(3) Impact of trade for most Americans? Ordered logit
<u>Panel A: Trade Hurts Jobs</u>			
Trade Hurts Jobs	0.239*** [0.043]	0.048*** [0.016]	-0.248*** [0.017]
Trade Hurts Jobs sans China	0.143** [0.071]	0.057** [0.025]	-0.203*** [0.026]
Test for equality, p-value:	[0.236]	[0.754]	[0.121]
Observations	4,617	4,617	4,617
(Pseudo) R-squared	0.153	0.048	0.072
<u>Panel B: Trade Helps Jobs</u>			
Trade Helps Jobs	0.069 [0.045]	0.030* [0.016]	-0.029* [0.017]
Trade Helps Jobs sans China	0.125 [0.077]	0.019 [0.024]	-0.021 [0.024]
Test for equality, p-value:	[0.534]	[0.715]	[0.786]
Observations	4,586	4,586	4,586
(Pseudo) R-squared	0.158	0.049	0.046
<u>Panel C: Trade Helps Prices</u>			
Trade Helps Prices	0.118*** [0.043]	0.027* [0.015]	-0.064*** [0.016]
Trade Helps Prices sans China	0.138*** [0.051]	0.007 [0.017]	-0.057*** [0.018]
Test for equality, p-value:	[0.669]	[0.212]	[0.667]
Observations	5,386	5,386	5,386
(Pseudo) R-squared	0.142	0.050	0.052
Individual, county, week, rand. order controls?	Y	Y	Y

Notes: Based on the Round 2 (2020), Round 3 (2021), and Round 4 (2022) samples; comprising respondents in the "Control" group who received no information treatment (the omitted category), as well as those who received the treatments listed in the respective panels. The dependent variable in Column 1 is the first principal component measure (from Column 6 of Table 4) constructed to be increasing in preferences for more limits on trade; that in Column 2 is a categorical variable for degree of agreement with the statement that the information received affected one's views on trade policy (1="Strongly disagree", 5="Strongly agree"); while that in Column 3 is a categorical variable asked post-treatment on views on the impact that trade has had for most Americans (1="Extremely bad", 5="Extremely good"). The controls included (but not reported) are as listed in the Table 3 footnotes, as well as Democrat and Republican dummies for the candidate supported in the last presidential election; Column 1 further includes the randomization order in which "More Limits on Imports" appeared in the "Most Preferred" list of 8 policies. Column 1 reports an OLS regression. Columns 2-3 report marginal effects from ordered logit regressions, on the predicted probability that either the fourth or fifth highest ordered category is selected as the response; all marginal effects are evaluated setting the initial values of the treatment dummies to zero, while setting all other right-hand side controls at their in-sample mean values. The p-value reported in each column is for a test of equality of the coefficients/marginal effects for the respective "with China" and "sans China" treatments. Standard errors are clustered by respondent county, and computed where necessary by the delta method; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

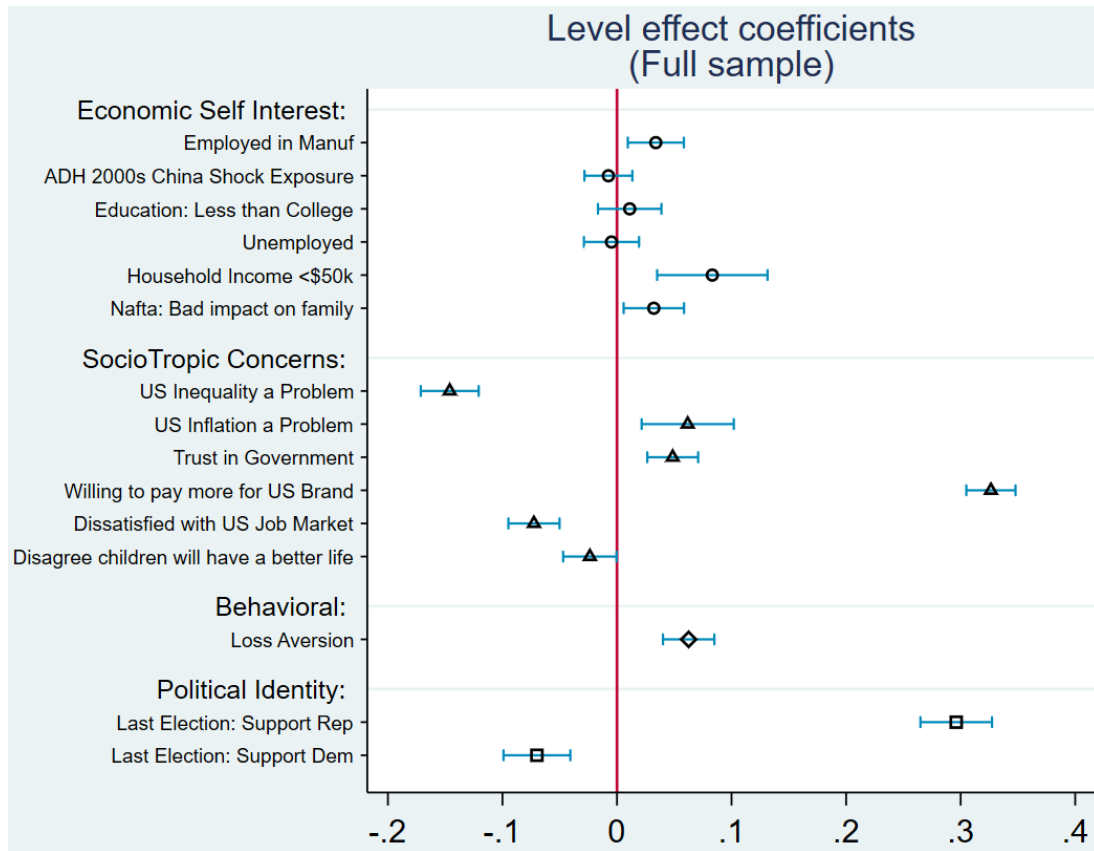
Appendix Table 14
Reasons for "More Limits on Imports": Comparing treatments "with" and "sans China"
(Pooled: Round 3, 2021; Round 4, 2022)

Dependent variable: (5=Strongly agree, 1=Strongly disagree)	(1)	(2)	(3)	(4)	(5)	(6)
	Agreement Score: Reason for "More Limits on Imports" as a Most Preferred Policy					
	OLS					
Treatments in sample:	Trade Hurts Jobs with/sans China	Trade Helps Jobs with/sans China		Trade Helps Prices with/sans China		
Omitted category:	Persuaded	Persuaded	Not persuaded	Not persuaded	Not persuaded	Not persuaded
Quality Concerns	-0.071 [0.054]	-0.011 [0.085]	0.102* [0.054]	0.009 [0.076]	0.324*** [0.055]	0.201** [0.078]
National Security	-0.259*** [0.054]	-0.092 [0.084]	-0.060 [0.057]	-0.224** [0.088]	0.077 [0.060]	0.034 [0.092]
Compete with Jobs	0.282*** [0.045]	0.327*** [0.072]	0.381*** [0.056]	0.297*** [0.079]	0.674*** [0.051]	0.590*** [0.077]
Concerns about imports from China	0.189*** [0.048]	0.181** [0.075]	0.516*** [0.059]	0.316*** [0.098]	0.665*** [0.057]	0.586*** [0.082]
Other reasons	0.009 [0.051]	0.049 [0.084]	0.100* [0.055]	-0.025 [0.085]	0.455*** [0.054]	0.316*** [0.083]
With China × Reason:						
Quality Concerns		-0.101 [0.113]		0.160 [0.100]		0.249** [0.103]
National Security		-0.282** [0.112]		0.282** [0.118]		0.087 [0.121]
Compete with Jobs		-0.077 [0.097]		0.145 [0.112]		0.170 [0.109]
Concerns about imports from China		0.014 [0.106]		0.346*** [0.121]		0.160 [0.105]
Other reasons		-0.068 [0.107]		0.215* [0.113]		0.282** [0.110]
Response Randomization Order	0.004 [0.009]	0.004 [0.009]	0.030*** [0.010]	0.029*** [0.010]	0.024** [0.009]	0.024** [0.009]
Individual fixed effects?	Y	Y	Y	Y	Y	Y
Observations	2,682	2,682	2,436	2,436	3,036	3,036
Number of respondents	447	447	406	406	506	506
R-squared	0.543	0.545	0.502	0.505	0.505	0.507

Notes: The regression sample comprises respondents in Round 3 (2021) and Round 4 (2022) who selected "More limits on imports" as a top three "Most preferred" policy out of the list of eight policies; Columns 1-2, 3-4, 5-6 comprise respectively the "Trade Hurts Jobs", "Trade Helps Jobs", and "Trade Helps Prices" treatment groups, and their associated "sans China" counterparts. The dependent variable in each column is the agreement score (on a scale of 1-5) with a given reason for selecting "More limits on imports". "With China" is a dummy variable equal to 1 if the information treatment received contained a mention of "China", i.e., is equal to zero for the "sans China" treatments. The omitted Reason category is as listed in each column. All columns control for individual fixed effects, as well as the reason randomization order. All regressions are run using OLS. Standard errors are clustered by respondent county; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

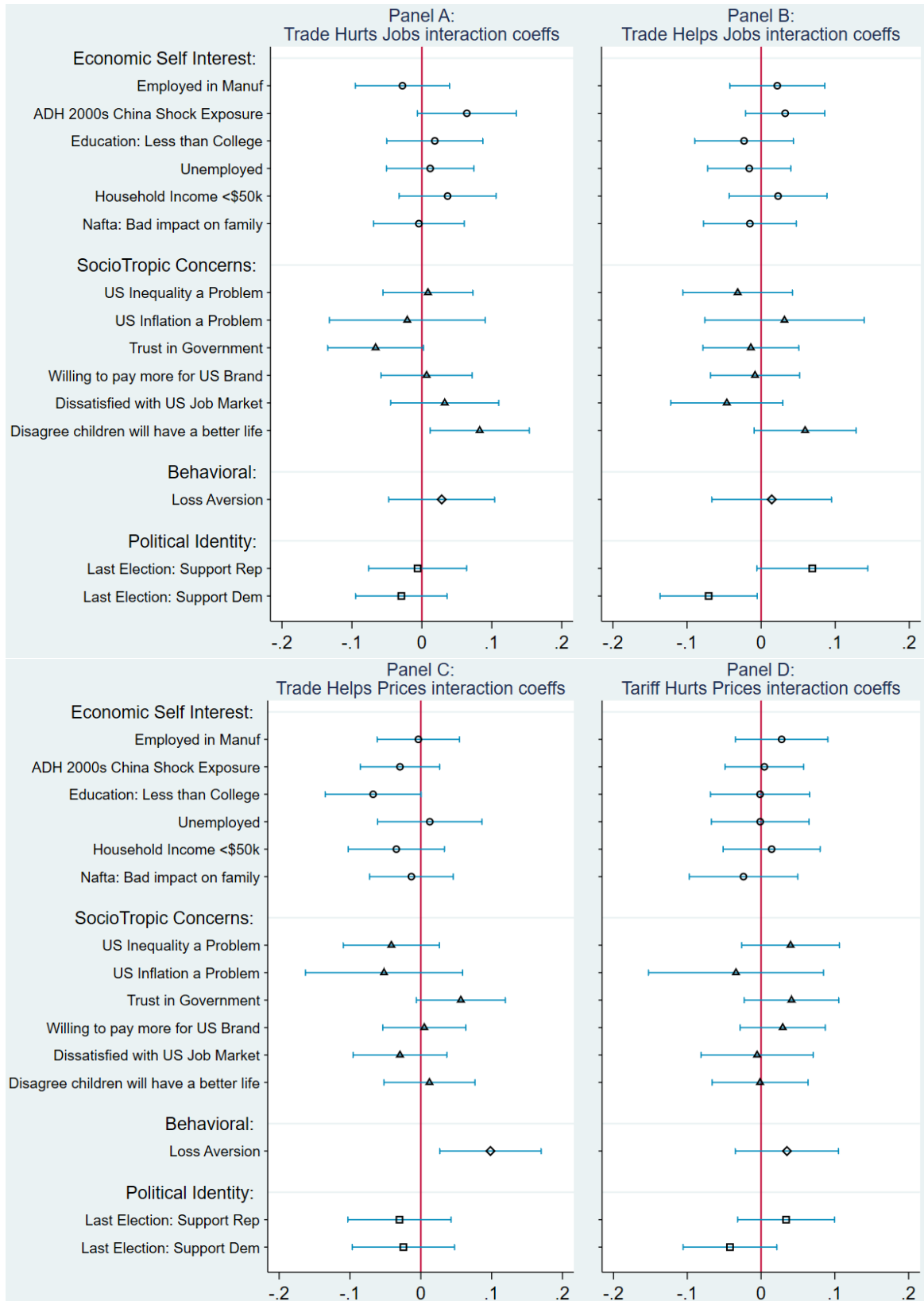
Appendix Figure 1

Exploring Mechanisms: Respondent Characteristics and Preferences for Protection (Level Effects, Full Sample)



Notes: Coefficient point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Each coefficient is from a separate OLS regression; sample comprises respondents in the “Control” group, and respondents in the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups, from Round 2 (2020), Round 3 (2021), and Round 4 (2022). Each respondent characteristic is expressed as a z-score.

Appendix Figure 2
Respondent Characteristics and Preferences for Protection (Interaction Effects, Full Sample)



Notes: Coefficient point estimates with 90% confidence intervals are illustrated; standard errors are clustered by respondent county. Each coefficient is from a separate OLS regression with treatment group indicators interacted with the respondent characteristic in question; sample comprises respondents in the “Control” group, and respondents in the “Trade Hurts Jobs”, “Trade Helps Jobs”, “Trade Helps Prices”, and “Tariff Hurts Prices” treatment groups, from Round 2 (2020), Round 3 (2021), and Round 4 (2022). Each respondent characteristic is expressed as a z-score.

