Learning About Trade

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Abstract

How do citizens form their opinions on international trade? Recent studies have challenged the assumption that economic self-interest is a key driving force behind individuals' trade attitudes. Using a survey experiment on a nationally representative sample of Americans, I show that despite widespread misperceptions, respondents are able to form more accurate beliefs, in a manner consistent with rational (Bayesian) updating, when given expert information about the economic consequences of trade. Moreover, information affects stated support for different trade policies only through its impact on beliefs. While individual trade preferences differ by party, race, and the identity of the trading partner, none of these factors lead to biased information processing. Nevertheless, the speed of learning does vary by gender, numeracy, prior trade knowledge, and the identity of the trading partner.

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1. Introduction

How do citizens form their opinions on international trade? In particular, what are the sources of public opposition to free trade policies? Conventional wisdom links individual trade preferences to economic self-interest, as these preferences are thought to reflect one's economic status as either a winner or loser from trade integration. The argument, which is derived from well-established economic theories, identifies economic losers based on their factor endowments or industry characteristics, with these losers more likely to hold negative views toward trade.[1] However, assumptions centered around economic self-interest have recently been challenged as micro-level observations fail to produce consistent evidence (Mansfield and Mutz, 2009; Oatley, 2017; Walter, 2021). Instead, a growing body of literature contends that non-economic factors, e.g. psychological and cultural factors, have driven public attitudes toward trade (Brutger and Rathbun, 2021; Edwards, 2006; Guisinger, 2017; Lü, Scheve and Slaughter, 2012; Margalit, 2012; Mutz, 2021).

Rather than disregarding the significance of economic self-interest, a related strand of literature suggests that the lack of empirical support for material self-interest can be attributed to misperceptions about the economic consequences of trade (Naoi, 2020; Rankin, 2001; Rho and Tomz, 2017). On the one hand, ordinary citizens often lack correct information about the distributional consequences of trade. On the other hand, even with access to this information, understanding its implications often presents a challenge. Yet the existing literature lacks a comprehensive understanding of the economic misperception argument. Specifically, it remains unclear whether individuals can form more accurate beliefs about the economic consequences of trade when presented with correct information, and furthermore, whether

[1] Two dominant models are the Stolper-Samuelson and the Ricardo-Viner theorems. The Stolper-Samuelson theorem suggests that owners of factors of production (labor and capital) in a nation that are scarce relative to the rest of the world will lose from trade and gain from protection. In the US context, trade liberalization will hurt low-skilled workers. According to the Ricardo-Viner model, trade benefits workers in exporting sectors and harms those in import-competing sectors (Rogowski, 1990).

these revised beliefs can, in turn, affect their opinions on trade.

In this article, I show that despite widespread misperceptions about the economic consequences of trade, Americans are capable of developing more accurate beliefs regarding these consequences in response to the right information. These updated beliefs also translate into changes in their trade policy choices. To this end, I conduct a survey experiment on a nationally representative sample of approximately 4,000 Americans to study how they learn about the economic impacts of the Chinese import shock. My experimental design features several distinct elements that represent a necessary departure from the existing literature on the effect of new information on trade opinions in survey experimental settings (Ardanaz, Murillo and Pinto, 2013; Hiscox, 2006; Jamal and Milner, 2019; Maria Schaffer and Spilker, 2019; Rho and Tomz, 2017). Firstly, to clearly distinguish between beliefs and stated policy choices, I ask respondents to indicate their preferred trade policy, either more restrictive or more liberal, and separately elicit their beliefs about the economic consequences of adopting a restrictive trade policy toward China, both before and after the information treatment.

Secondly, to ensure the effectiveness of the information treatment, I present participants with the best available estimates of the economic consequences of the Chinese import shock. These estimates, based on Autor, Dorn and Hanson (2013), are presented in a context devoid of any potential sources of bias. In addition, the information is presented as exact point estimates of the consequences. This format, mirrored in participants' prior and posterior beliefs, strengthens the link between the provided information and their resulting beliefs, further enhancing the effectiveness of the information treatment. Finally, to causally identify the effect of information and assess how individuals learn based on its precision, I randomly assign respondents to various groups. While a control group receives no information, the treatment groups are exposed to one or both of two types of information that differ in their level of precision. The more precise information includes the specific consequences of the import shock for the economic group to which a participant belongs. By contrast, the less precise signal pertains to the general economic consequences at the US national level.

Furthermore, a third group is provided with both types of information. This allows me to examine how well individuals can discern and draw conclusions from the more precise information, and to determine whether respondents use the general information for detailed inferences or simply as a heuristic for updating their beliefs.

I find that a significant number of Americans hold incorrect beliefs about the economic consequences of trade. Despite such prevailing misconceptions, respondents update their beliefs about the economic consequences of trade rationally, consistent with Bayesian updating: individuals who are less informed or highly uncertain about their prior beliefs tend to revise them more in response to new information. Moreover, it is through this sole pathway of updated beliefs that information can influence trade policy choices. When evaluating different types of information, my results suggest that participants place a similar value on both the precise, specific information and the less precise, general information; nonetheless, they give slightly more weight to the precise one. Furthermore, individuals use the general information as a shortcut to derive their individual-specific beliefs.

In categorizing trade preferences by party, race, and the identity of the trading partner, I find that none of these factors lead to biased information processing, which would cause individuals to revise their beliefs in a way that is inconsistent with Bayes' rule. For example, I show that Democrats and Republicans, despite having divergent prior beliefs and prior trade policy choices, update their beliefs in ways that are indistinguishable from each other. Similarly, white and non-white respondents process information in the same way, even though race is an important predictor of trade preferences. The identity of the trading partner, however, leads to a slightly different picture. When presented with information that randomizes the trading partner as either China or a hypothetical low-income country that is a major source of US imports, individuals show a bias against China as a trading partner. Nevertheless, they still process information in an unbiased manner, albeit at a slower rate when China is the trading partner. Beyond the identity of the trading partner, I document additional individual heterogeneity in learning rates based on gender, trade knowledge, and numeracy. Females, numerate individuals, and those with greater trade knowledge tend to be more responsive to new information.

My findings provide a richer understanding of how people form their trade opinions. Firstly, unlike some experiments that study the effect of information on stated policy choices through a black box, my research explicitly distinguishes between beliefs and individual policy choices. In doing so, it clearly identifies the underlying mechanism, highlighting the role of beliefs in linking information to policy choices. I find that information affects people's policy choices solely by changing their beliefs.[2] Given the growing scholarly interest and mixed evidence on the impact of information on stated policy choices, my design suggests that highlighting the role of beliefs is crucial to understanding the sources of this inconsistency.[3]

Secondly, I explore a relatively understudied source of economic misperceptions about trade by examining whether they arise from the process of belief formation. Specifically, I examine whether individuals are able to develop more accurate beliefs in response to expert information about the economic consequences of trade. I find that individuals update their beliefs in line with Bayesian updating, modifying them based on the new information they receive (Barrera et al., 2020; Guess and Coppock, 2020; Nyhan et al., 2020). This contrasts with some empirical studies that find either belief updating contrary to information, thereby reinforcing misperceptions (Nyhan and Reifler, 2010), or belief polarization, where different groups update their beliefs in opposite directions (Lord, Ross and Lepper, 1979; Taber

[2] This finding contrasts with some misperception correction studies, where corrective information affects individuals' beliefs but not necessarily their stated preferences (Barrera et al., 2020; Hopkins, Sides and Citrin, 2019; Nyhan et al., 2020).

[3] Research provides mixed evidence on the impact of information on individual stated preferences. Some studies suggest that information plays a crucial role in shaping public opinion (Boudreau and MacKenzie, 2014; Bullock, 2011; Chong and Druckman, 2010; Gilens, 2001). In contrast, other research finds "muted consequences," suggesting that information has no effect on stated preferences (Hopkins, Sides and Citrin, 2019; Kuklinski, Quirk et al., 2000; Nyhan et al., 2020). See Nyhan and Reifler (2010) and Druckman and Lupia (2016) for a more detailed summary.

and Lodge, 2006).[4] Both phenomena are argued in scholarly discourse to be often driven by a process known as "motivated reasoning." I do not observe any patterns of belief polarization along party or racial lines, nor in relation to the identity of trading partners, echoing Hill (2017)'s conclusion that there is no belief polarization, for information with obvious consequences for a party's reputation. The only variation I observe across individuals relates to the learning rate, with some demographic groups processing information at a faster rate.[5]

Finally, my study contributes the existing debate about whether economic (Curtis, Jupille and Leblang, 2014; Fordham and Kleinberg, 2012; Jamal and Milner, 2019; Maria Schaffer and Spilker, 2019; Owen and Johnston, 2017; Rho and Tomz, 2017) or non-economic (Brutger and Rathbun, 2021; Edwards, 2006; Guisinger, 2017; Lü, Scheve and Slaughter, 2012; Margalit, 2012; Mutz, 2021; Mutz and Kim, 2017) concerns drive preferences for globalization. My findings underscore that economic factors are an important consideration for citizens; this is demonstrated by the fact that individuals rationally update their beliefs about the economic consequences of trade, and these updated beliefs subsequently affect people's trade policy choices. With respect to the non-economic component, my findings indicate that individual views on international trade are divided along party and racial lines, as well as between different trading partners. This reflects pre-existing cultural, psychological, ideological, and identity divisions that are non-material in nature. Nevertheless, none of the factors lead to biased information processing. Despite having divergent preferences, respondents rationally update their beliefs about the economic consequences of the trade shock. These results call for a more comprehensive understanding of trade opinion formation by fully unpacking the

[4] Find Druckman and McGrath (2019) for a more detailed categorization of the outcome of information processing. Find Guess and Coppock (2020) for a detailed discussion of belief polarization.

[5] This finding is consistent with the economic literature, which has also documented similar patterns of heterogeneous information processing Armantier et al. (2016) find that female respondents are more responsive to information than males. Fuster et al. (2022)'s results show that literate respondents update more in response to new information.

role of both economic and non-economic factors.

The remainder of the article proceeds as follows: I begin by introducing the data collection process, explaining the randomization, and outlining the detailed experimental design. In the subsequent section, I examine if individuals are initially uninformed about the economic consequences of trade, a necessary condition for the effectiveness of the information treatment. In Section 4, I explore the impact of information on beliefs. Following this, Section 5 shows how these updated beliefs influence policy choices. While the previous sections shed light on the role of economic factors in individual trade policy choices, Section 6 investigates the impact of non-economic factors on trade policy choices and information processing. In the final section, I discuss the broader implications of the study and conclude.

2. Experimental Design

I conducted a survey experiment on a nationally representative sample of 4,001 Americans in July of 2022.[6] [7] The sample was recruited through the survey firm Cint, reflecting the demographic distribution of the US population in terms of gender, age, and region. I oversampled respondents with a college degree, who comprised half of the sample, because the beliefs elicited from respondents and the information they received were tailored to their level of education (college or non-college) and sector of employment (manufacturing or non-manufacturing).[8]

My main experiment consists of four treatment arms, each of which involves five stages.[9] The treatment arms differ in the information about the trading partner (China or a hypo-

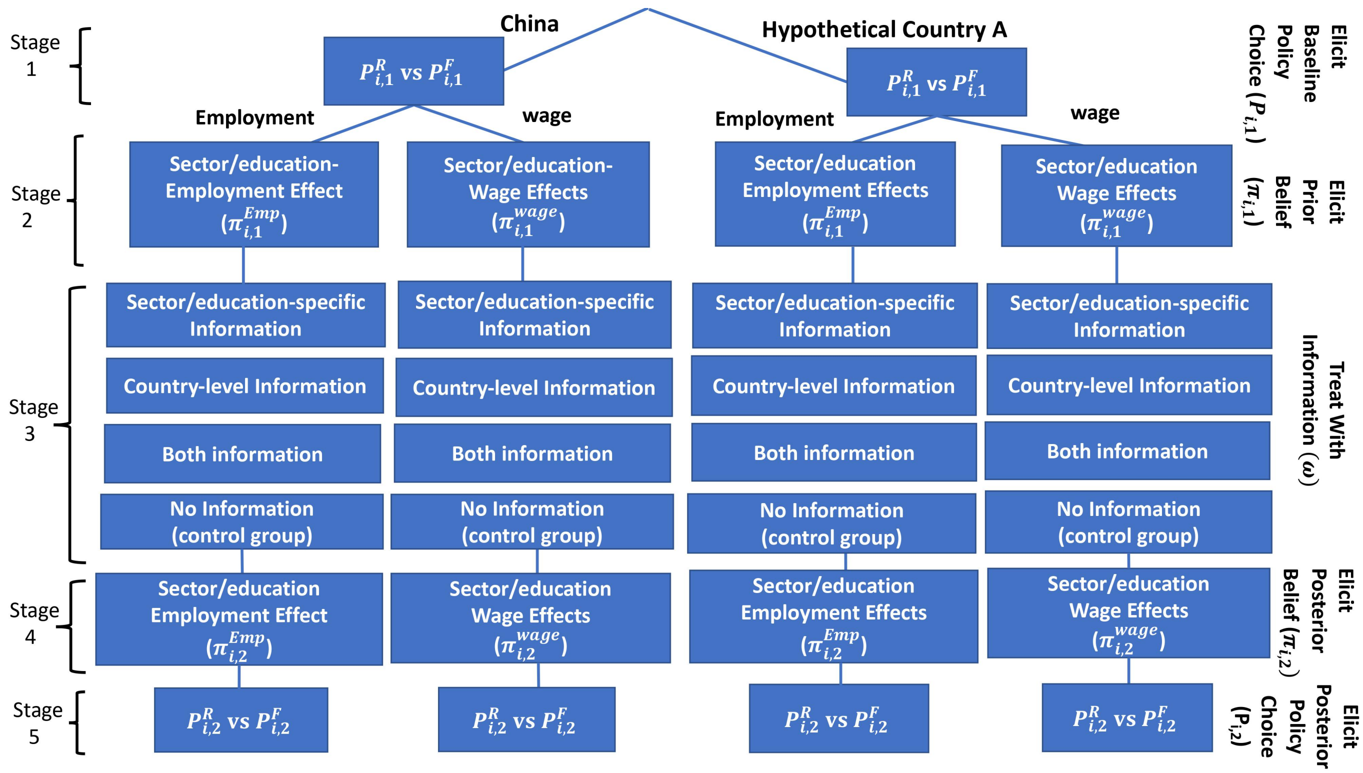
[6] I pre-registered the study at `https://doi.org/10.17605/OSF.IO/AVWP7`.

[7] There are two attention checks throughout the survey; if respondents fail either, they are removed from the survey. The 4001 sample consists entirely of respondents who pass the attention checks.

[8] Ideally, I would also prefer that 50% of the respondents in the sample come from the manufacturing sector, but the survey firm lacks the profiling information to ensure this.

[9] Before and after the main experiment, I asked participants to answer a battery of demographic, political, news consumption, and trade-related questions as part of the survey.

Figure 1: Experimental Design



thetical country) and in the economic consequences (employment or weekly wages) of the import shock, as detailed below. The five stages of each treatment arm begin with eliciting participants' prior trade policy choices and beliefs. This is followed by the administration of an information treatment, and then a reassessment of their posterior beliefs and policy choices. Figure 1 summarizes the experimental design that is inspired by Armantier et al. (2016).

The entire experiment involves three levels of randomization. Firstly, to explore whether individuals harbor a bias against China as a trading partner, and if this bias systematically affects their information processing, I began the experiment by randomly assigning participants to one of the trading partners: either China or a hypothetical country. For the hypothetical country, I asked subjects to imagine a "hypothetical country A" — an unidentified nation designed to mirror China in key aspects, particularly as a significant source of US imports from low-income countries, predominantly in manufactured goods.[10] Hereafter, I will use the terms "China arm" and "hypothetical arm" to refer to the groupings of treatment arms that are associated with the same trading partner. Secondly, after the initial randomization, respondents were further divided in the second stage, where they were asked to share their prior beliefs and then received information about the employment or weekly wage consequences of the import shock from their assigned country. This second level of randomization was designed to assess the effect of these economic consequences on belief updating. In a similar vein to the previous labels, I will refer to the groupings of the treatment arms that share the same economic consequences as either the "employment arm" or the "wage arm." The above categorization defines the general distinction of the four treatment arms. Moving forward, I will use combined labels such as "China-employment arm" or "hypothetical-wage arm" to refer to each individual treatment arm. As will become apparent throughout this section, except for the two aforementioned randomizations, each treatment arm mirrors the others.

Last but not least, the final randomization took place in the third stage, which concerns the specific information treatment. Participants were randomly assigned with equal probability to one of the treatment groups or a control group to examine the causal effect of the information on their updating beliefs. As I will discuss further, within the treatment groups, one group received a precise message, another a less precise one. The third group, however, was provided both types of messages. This was done to evaluate whether participants learn differently based on the type of information. In the subsequent sections, I will detail the specific design of each stage, along with the associated randomizations.

Stage 1: Prior Policy Choices ($P_{i,1}$). In the first stage, I asked participants to select their preferred trade policy with the corresponding trading partner, either China or the hypothetical country A.[11] One option was relatively pro-trade: "US trade policies should

[10] Please see Appendix A.1 for detailed language.

[11] See Appendix A.1 for the introductory script and descriptions that respondents read before making their trade policy choices.

aim to keep imports from China (or the hypothetical country A) at the current level," while the alternative was more restrictive: "US trade policies should aim to reduce imports from China (the hypothetical country A) by 30%."[12] [13] Then the experiment proceeded to the second stage.

Stage 2: Prior belief ($\pi_{i,1}^{S/E}$). My measure of individuals' beliefs is their perception of the economic consequences of the import shock. As mentioned earlier, in the second stage, I randomly assigned subjects to one of two questions measuring their prior beliefs about different economic consequences of the import shock. The first question asked about employment: "By what percentage do you think the number of employed individuals in your sector (manufacturing/non-manufacturing) who have the same educational background (bachelor's degree or higher/no bachelor's degree) as you would change if there is a 30% reduction in US imports from China (the hypothetical country A)?" The second was identical to the first except for replacing "number of employed individuals" with "weekly wages." I customized the sector and educational background information in parentheses based on the demographic questions respondents answered before the main experiment. The question was followed by a slider that ranged from -10% to 10%, allowing subjects to pin down their answers to point estimates.[14] I instructed respondents to provide their answers that were the best approximation of the impact, which would be in percentage forms.

After eliciting their prior predictions, I asked participants how confident they are about

[12] I derive the percentage, 30%, from the empirical results of Autor, Dorn and Hanson (2013). It approximates the estimated percentage increase in Chinese imports to the US from 1990 to 2007. The 30% level is used consistently throughout the experiment. It is the value I asked subjects to consider when forming their beliefs and the information they received. This consistency ensures that the information subjects observe is directly related to the effect they are asked to predict and the policy they choose.

[13] I chose the expression "reduce 30%" rather than "increase 30%" because it is more reasonable for policymakers to set a goal of reducing imports, and it is more natural for citizens to imagine the consequences in that direction.

[14] I selected this range because it is a reasonable bound on the economic consequences of an import shock. It also avoids the issues of outliers that can bias the results.

their predictions. It is then followed by five numeracy assessment questions derived from Armantier et al. (2016) and Fuster et al. (2022) to evaluate subjects' level of numeracy.[15]

Stage 3: Information treatment (T_i). I randomly assigned participants to either one of three treatment groups, each receiving different information, or to a control group, which received no information. As previously noted, I obtain the information from Autor, Dorn and Hanson (2013) and treat them as the best available estimates of the economic consequences of the Chinese import shock. The benefit of delivering credible information is to increase external validity and prevent deception (Boudreau and MacKenzie, 2014). It is critical, especially for the purpose of this study, that the subjects perceive the information as credible so it can significantly impact their beliefs (Armantier et al., 2016).[16]

The first information treatment group is known as the Sector/Education-specific Information Group, or S/E-specific Information Group ($T_i^{S/E}$), and it provides what I consider to be a more precise message. Depending on the specific economic consequences they were asked to predict in the second stage, respondents in this group were given information about their sector/education-specific effect of Chinese (or the hypothetical country A's) import shocks, matching their sectors of employment (manufacturing/non-manufacturing) and education level (bachelor's degree or higher/no bachelor's degree).[17] Consequently, I further divided my subjects within this treatment group into four groups receiving different information based on their employment sector and educational background. The information provided directly answers the questions posed in the second stage: respondents were informed of the effect through a point estimate, and also of the uncertainty about the effect, represented by a 90% confidence interval.

[15]They attribute their questions to Lipkus, Samsa and Rimer (2001). See Appendix A.5.1 for questions.

[16]At the end of the survey, I also asked respondents to indicate their level of agreement with the statement,"In general, I trust the credibility of people referred to as researchers."This question is another measure of participants' perceptions of the credibility of the information.

[17]Each piece of information is identical for the hypothetical arm, with the exception of "China" being replaced by"the hypothetical country A."

For example, I provided the following tailored information to a subject in the China-employment arm who is employed in the manufacturing sector and has a bachelor's degree: "Researchers estimate that a 30% reduction in US imports from China would increase the number of employed individuals in your sector (manufacturing) who have the same educational background (bachelor's degree or higher) as you by 3.99%. Researchers cannot predict the actual increase with certainty. However, they are very (90%) confident that the actual increase in the number of employed individuals in your sector who have the same educational background as you will be between 2.05% and 5.93%."[18]

The second treatment group is called the Country-level Information Group ($T_i^{Country}$), where participants received information about the overall employment or wage effects of the Chinese import shock at the US national level. This is considered a less precise message compared to the S/E-specific information. For instance, the following information was provided to participants in the China-employment arm: "Researchers estimate that a 30% reduction in US imports from China would increase the number of employed individuals in the US by 4.92%. Researchers cannot predict the actual increase with certainty. However, they are very (90%) confident that the actual increase in the number of employed individuals in the US will be between 3.07% and 6.78%."[19] In contrast to the S/E-specific Information Group, all respondents in this treatment group share this information.

For the third treatment group, referred to as the Both Information Group ($T_i^{Country} \times T_i^{S/E}$), subjects obtained both S/E-specific and country-level information, with the order of information being randomized. Similar to the S/E-specific information, I divided participants into four subgroups based on their individual characteristics. These subgroups received their S/E-specific information along with national-level information that was consistent across all subgroups. In the control group, no information was provided to participants.

Stage 4: Posterior belief ($\pi_{i,2}^{S/E}$). The fourth stage repeats the second stage, where I elicit respondents' posterior beliefs and inquire about the uncertainty regarding their predictions.

[18]See Appendix A.4.1 for the remaining information on this treatment group.

[19]See Appendix A4.2 for the information regarding the wage arm.

Stage 5: Posterior Policy Choice ($P_{i,2}$). In the fifth stage, I asked respondents to restate their choice between two trade policies, as in Stage 1.

3. Do Americans Hold Misperceptions About Trade?

For the provided information to have an effect on respondents' beliefs, it is essential that they do not already have complete knowledge of the experts' best estimates of the impact of trade (Armantier et al., 2016). The first puzzle I address is whether Americans have inaccurate beliefs about the economic consequences of the import shock.

First, I compare the signs of respondents' prior beliefs with the information presented in the S/E-specific Information Group, which I regard as the best available estimate of the sector/education-specific effects of the import shock. Upon this comparison, I find that 43% of respondents hold incorrect beliefs about the direction of the effects. In other words, this is the proportion of those who mistakenly believe that they are winners or losers due to imports, when in fact, the opposite is true.

Secondly, I leverage the advantage of eliciting beliefs as point estimates. This allows me to measure the *prior belief gap*, which is the distance between the estimate of S/E-specific consequences and respondents' prior beliefs, i.e., S/E-specific effects minus prior S/E-specific beliefs. This allows me to obtain a more accurate understanding of how well-informed respondents are about their S/E-specific consequences of the import shock. Table 1 presents summary statistics comparing the treatment group to the control group in both employment and wage arms, including the prior belief gap and other variables of interest. There are no statistically significant differences between the treatment and control groups in either the employment or wage arms in terms of the prior belief gap, the absolute prior belief gap, prior policy choice, or prior belief, suggesting that the sample was well-randomized.

The average prior belief gap in the employment arm is -0.60 percentage points for the control group and -0.44 percentage points for the treatment group, while in the wage arm it is

-0.73 and -0.86 percentage points, respectively. This suggests that respondents overestimate the impact of the import shock on employment and weekly wages. The modest size indicates that the positive and negative belief gaps cancel each other out, and we need to evaluate the distance using the absolute value. According to Table 1, respondents' prior beliefs are on average 3.01 (2.63) percentage points away from the employment (wage) effects in the control and 2.97 (2.66) percentage points away in the treatment, which are more than 3 standard deviations apart. Combining the evidence regarding incorrect beliefs about the direction of the effects, I conclude that a substantial proportion of individuals hold misperceptions about the magnitude and direction of the economic consequences of the trade shock. This, according to Armantier et al. (2016), is a necessary condition for information treatments to be effective.

4. The Effect of Information on Beliefs

Given the widespread misperceptions about the economic consequences of the import shock discussed in the previous section, the next question I address is whether individuals can rationally learn the relevant information. Specifically, I examine whether individuals update their beliefs in response to new information, consistent with Bayesian updating. Firstly, I compute the *belief update* as the difference between respondents' posterior and prior beliefs about their sector/education-specific effects. It is a measure of how much respondents change their beliefs over the course of the experiment. Table 1 provides an overview of the belief update and its absolute value. Since participants update their beliefs in both positive and negative directions, the absolute value: *absolute belief update*, reflects the magnitude of the revisions. The treatment groups show significantly greater absolute belief updates than the control group, with the employment (wage) arm seeing an update of 2.60 (2.35) percentage points, while the control group experience only 1.61 (1.53) percentage points. This indicates that learning is occurring.

Table 1: Average Prior Belief, Belief Gap and Belief Update

	Control	Treatment
Employment Arm		
Number of Observations	506	1496
% Prior Policy Choice = 1	43%	42%
Prior Belief	1.57	1.49
Prior Belief Gap	-0.60	-0.44
Absolute Prior Belief Gap	3.01	2.97
Belief Update (Posterior-Prior)	-0.14	0.05
Absolute Update	1.61	2.60***
Posterior Belief	1.43	1.54
% Posterior Policy Choice = 1	43%	35%***
Wage Arm		
Number of Observations	506	1493
% Prior Policy Choice = 1	43%	41%
Prior Belief	1.36	1.48
Prior Belief Gap	-0.73	-0.86
Absolute Prior Belief Gap	2.63	2.66
Belief Update (Posterior-Prior)	-0.16	-0.01
Absolute Update	1.53	2.35***
Posterior Belief	1.21	1.47
% Posterior Policy Choice = 1	45%	35%***

Note: Compare the treatment with the control. T-test for equality of means & Z-test for equality of proportions. Significant at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The treatment in this Table comprises the three treatment groups (the Country-level, the S/E-specific, and the Both Information Group). Policy Choice = 1 if respondents select the policy to keep imports from China (the hypothetical country A) at the current level. See Appendix B.1 for detailed summary statistics comparing control with each treatment group.

The next question arises as to whether respondents learn rationally according to Bayesian updating. Assuming normally distributed beliefs, I simplify the average belief update in the Bayesian paradigm by:[20]

$$Posterior - Prior = (Information - Prior) \times \left(\frac{Variance(Prior)}{Variance(Prior) + Variance(Information)}\right) \tag{1}$$

According to Equation 1, the average belief update depends on (a) the prior belief gap, (b) the prior belief variance, and (c) the information variance. I will first examine the relationship between the prior belief gap and the belief update. I will then examine the role of two other elements: $Variance(Prior)$ and $Variance(Information)$.

Equation 1 suggests that the belief update is positively related to the prior belief gap. In other words, according to Bayes' rule, I expect that respondents who overestimate (underestimate) the sector/education-specific consequences to modify their beliefs down (up) in light of the provided information. The blue dots in Figure 2 are the subjects who update their beliefs according to Bayes' theorem. They outnumber those who update their beliefs opposite to the information (gray dots) and those who do not update (red dots), especially in the three treatment groups. Consistent positive trends across treatment groups further buttress the finding that respondents update their beliefs according to Bayesian updating across treatment groups.

In the control groups, participants receive no information at Stage 3. Despite having a positive slope, the fitted line in Figure 2 is flatter for the control group than for any of the treatment groups. In addition, the control group also has more points scattered on or near the zero belief update line, indicating that a larger proportion of individuals made no or minimal revisions. The moderate upward trend can be explained by the following

[20] I obtain the equation from Box 1 of Druckman and McGrath (2019) and display it in a manner inspired by Armantier et al. (2016).

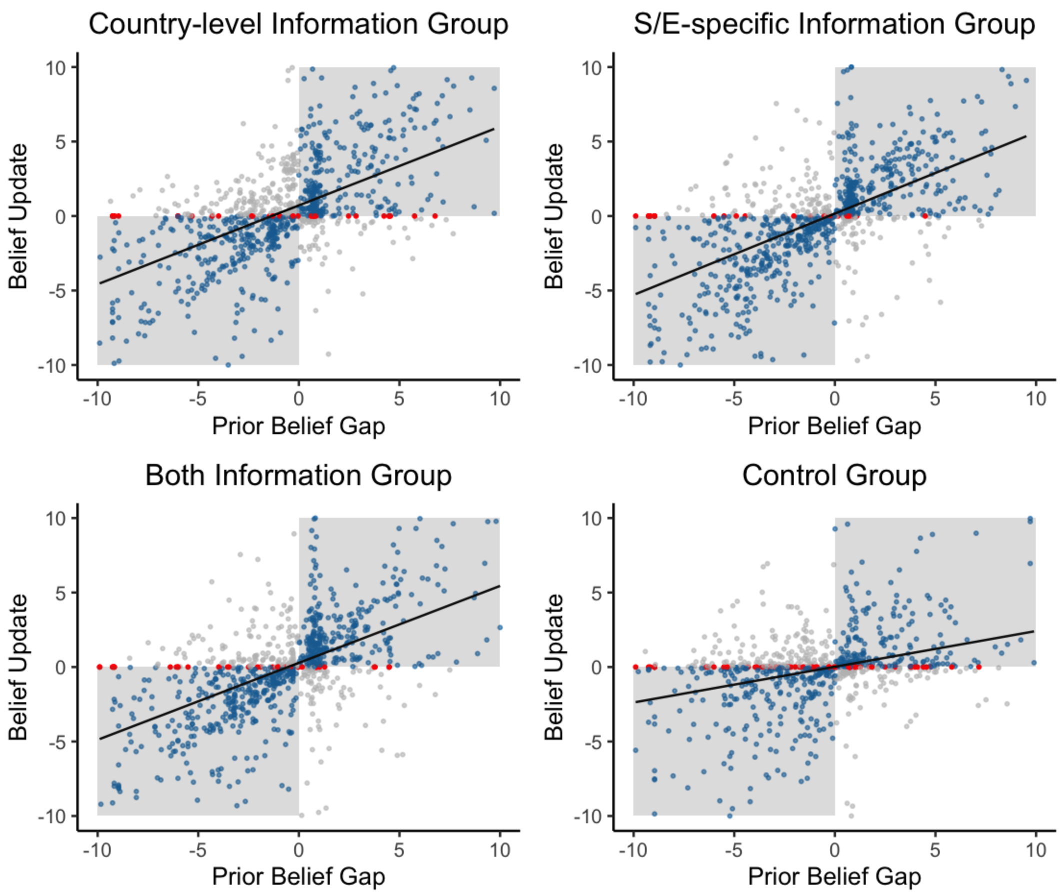
considerations: firstly, it may be an indication of self-correction, given the time lag between Stages 2 and 4 when respondents provide their prior and posterior beliefs. The pattern of self-correction is further supported by Figure 3, which shows that respondents with a high level of uncertainty about their prior beliefs self-correct more than their low-uncertainty counterparts in the control group. Secondly, the upward trend in the control group could be the result of regression to the mean.

Furthermore, I study the effect of information on beliefs using the following regression analysis:

$$\begin{aligned}\Delta\pi_i =& \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3 (T_i^{Country} \times T_i^{S/E}) + \gamma_1 (T_i^{Country} \times \Delta\omega_i) \\ &+ \gamma_2 (T_i^{S/E} \times \Delta\omega_i) + \gamma_3 (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \epsilon_i\end{aligned} \tag{2}$$

In Equation 2, the dependent variable of interest is $\Delta\pi_i$, the belief update, which measures the difference between individuals' posterior and prior beliefs about their sector/education-specific consequences ($\pi_{i,2}^{S/E} - \pi_{i,1}^{S/E}$). $\Delta\omega_i$ represents the prior belief gap that I introduced in the preceding section. This variable captures the gap between the actual sector/education-specific effects and individuals' prior beliefs ($\omega_i^{S/E} - \pi_{i,1}^{S/E}$).

T_is are indicator variables that equal to 1 if respondents belong to the S/E-specific Information Group ($T_i^{S/E}$), the Country-level Information Group ($T_i^{Country}$), or the Both Information Group ($T_i^{Country} \times T_i^{S/E}$). Due to the treatment assignment, only participants in the S/E-specific Information or the Both Information Groups were able to precisely observe their prior belief gaps. Respondents in the Country-level Information Group received information about the aggregate impact at the national level. Since it is less straightforward for respondents to connect country-level information to their beliefs about sector/education-specific impacts, I consider the country-level information to be an imperfect (noisy) message concerning these particular impacts. According to the Bayesian framework, the variance of this message is larger than that of the S/E-specific information. It is intriguing to explore



Note: The upper left panel shows the scatter plot of the prior belief gap (x-axis) and the belief update (y-axis) for all respondents in the Country-level Treatment Group. The upper right, bottom left, and bottom right represent the S/E-specific Treatment, Both Treatment, and Control groups, respectively. The range for the x- and y-axes is limited to -10 to 10 to exclude outliers and enhance visualization; the patterns observed remain consistent even when considering the full range of data. See Appendix B.2 for the graph with the full range of data. Blue dots in the shaded quadrants indicate respondents who updated their beliefs in the direction of the information provided. This is demonstrated by those with a positive (negative) belief gap, who updated their belief in a positive (negative) direction, thereby aligning it more closely with the provided information. On the contrary, gray dots represent those who update their beliefs in the opposite direction to the information provided. Red dots indicate those who do not update their beliefs.

Figure 2: Effects of Information on Beliefs

how participants learn from this noisy information.

γs are coefficients of interest that capture marginal effects of information treatments on belief updates with regard to belief gaps. According to the Bayesian framework, I expect γ_2 to be positive, implying that respondents with larger belief gaps adjust their beliefs more in response to S/E-specific information. I expect γ_3 to be 0, since there is no additional information given in this treatment group. However, in practice, γ_3 can still be positive or negative. This suggests that when individuals are presented with two pieces of information, they may update their beliefs to a greater or lesser extent than the combined effects of receiving each piece of information separately. Nevertheless, I expect a positive sign for $\gamma_1+\gamma_2+\gamma_3$, indicating Bayesian learning in the Both Information Group. The sign of γ_1 is less evident in this context, as it measures how respondents learn about their sector/education-specific impacts from a noisy signal concerning their belief gaps.[21] The presence of γ_1 with a positive sign indicates Bayesian updating.

I estimate Equation 2 using the ordinary least squares (OLS) regression. Since both the dependent variable ($\Delta\pi_i$) and the independent variable of interest ($\Delta\omega_i$) represent the deviations of the posterior belief and the actual S/E-specific information from the prior belief, respectively, the OLS regression accounts for individual heterogeneity with respect to the prior beliefs. Panel A of Table 2 shows the regression results for the full sample and for each separated treatment arm.

Column 5 is the regression results for the entire sample. In Column 5, the coefficients that capture how the effects of information treatments on belief updates vary with belief gaps (γ_1, γ_2, and $\gamma_1+\gamma_2+\gamma_3$) are all positive and statistically significant. These results indicate that individuals with larger belief gaps update their beliefs more in response to new information, and that this pattern is consistent across different informational signals. A one percentage point increase in the belief gap is associated with 0.65, 0.67, and 0.60 percentage points of belief updates, respectively, for participants in the Country-level Information Group, the S/E-specific Information Group, and the Both Information Group. As illustrated in Figure 2, there is a general tendency for participants to update their beliefs in the direction of the information, taking into account their prior belief gaps, which is consistent with Bayesian learning. Furthermore, this pattern is consistent across the China, hypothetical, wage, and employment arms, as shown in Columns 1 - 4 of Table 2.[22]

[21]The belief gap is unobserved by the participants, but observed by the researcher.

[22]In addition, as I show in the Appendix B.3, this pattern remains consistent across treatment arms

Table 2: The Effect of Information and Prior Uncertainty on Beliefs Across Treatment Groups Dependent Variable: the belief update ($\Delta\pi_i$)

A: The Effect of Information on Beliefs					
Coefficient	China Arm (1)	Hypothetical Arm (2)	Employment Arm (3)	Wage Arm (4)	Full Sample (5)
Ctry-level Info (γ_1)	0.63 [0.56, 0.70]	0.67 [0.60, 0.74]	0.56 [0.49, 0.63]	0.74 [0.67, 0.81]	0.65 [0.60, 0.70]
S/E-specific Info (γ_2)	0.60 [0.54, 0.67]	0.74 [0.67, 0.81]	0.74 [0.67, 0.80]	0.59 [0.52, 0.66]	0.67 [0.62, 0.71]
Both Info ($\gamma_1 + \gamma_2 + \gamma_3$)	0.57 [0.50, 0.64]	0.63 [0.56, 0.70]	0.58 [0.51, 0.65]	0.63 [0.55, 0.70]	0.60 [0.55, 0.65]
B: The Effect of Prior Uncertainty & Information on Beliefs					
	(6)	(7)	(8)	(9)	(10)
High − Low: Ctry-level (γ_{U1})	0.05 [-0.09, 0.19]	0.04 [-0.10, 0.19]	0.11 [-0.03, 0.25]	-0.05 [-0.19, 0.09]	0.05 [-0.05, 0.15]
High − Low: S/E-specific (γ_{U2})	0.18 [0.05, 0.31]	0.16 [0.01, 0.31]	0.08 [-0.06, 0.21]	0.28 [0.14, 0.43]	0.17 [0.07, 0.27]
High − Low: Both ($\gamma_{U1} + \gamma_{U2} + \gamma_{U3}$)	0.19 [0.04, 0.33]	0.12 [-0.03, 0.27]	0.08 [-0.06, 0.22]	0.24 [0.09, 0.39]	0.15 [0.05, 0.25]
High: Ctry-level ($\gamma_1 + \gamma_{U1}$)	0.66 [0.56, 0.76]	0.69 [0.59, 0.79]	0.62 [0.51, 0.72]	0.72 [0.63, 0.82]	0.67 [0.60, 0.75]
High: S/E-specific ($\gamma_2 + \gamma_{U2}$)	0.70 [0.61, 0.79]	0.82 [0.72, 0.93]	0.78 [0.69, 0.87]	0.75 [0.65, 0.85]	0.76 [0.69, 0.82]
High: Both (γ_{1+2+3}+γ_{U1+2+3})	0.69 [0.58, 0.80]	0.69 [0.59, 0.79]	0.63 [0.53, 0.74]	0.76 [0.66, 0.87]	0.69 [0.62, 0.76]
N	2025	1976	2002	1999	4001

Note: Ordinary least squares (OLS) regression. 95% confidence levels in parentheses. The complete table, including the results of the subsamples: the China-employment arm, the hypothetical-employment arm, the China-wage arm, and the hypothetical-wage arm, can be found in the Appendix B.3. Full regression outputs for Panel A are in Appendix B.3.1. The equation for Panel A is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \epsilon_i$ (2). The equation for Panel B is obtained by fully interacting Equation 2 in Panel A with $Uncertain_i$, that is, by adding several additional terms to Equation 2: (i) $\beta_{U1}(T_i^{Country} \times Uncertain_i)$; (ii) $\beta_{U2}(T_i^{S/E} \times Uncertain_i)$; (iii) $\beta_{U3}(T_i^{Country} \times T_i^{S/E} \times Uncertain_i)$; (iv) $\gamma_{U1}(T_i^{Country} \times \Delta\omega_i \times Uncertain_i)$; (v) $\gamma_{U2}(T_i^{S/E} \times \Delta\omega_i \times Uncertain_i)$; (vi) $\gamma_{U3}(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i \times Uncertain_i)$; (vii) $\alpha_U Uncertain_i$. Full regression outputs for Panel B are in Appendix B.3.2.

when the sample is further divided into smaller subsamples: the China-employment arm, the hypothetical-employment arm, the China-wage arm, and the hypothetical-wage arm.

The positive and statistically significant γ_1 indicates that individuals incorporate country-level information to update their S/E-specific beliefs in a way that is consistent with Bayes' theorem. As noted previously, country-level information has greater variance than S/E-specific information, as subjects are less certain about how to relate it to their prior S/E-specific beliefs. Returning to Equation 1, individuals, on average, update their beliefs less in response to information with greater variance. As a consequence, I expect the magnitude of γ_1 to be smaller than γ_2, as shown by the full sample results in column 5 of Table 2.

However, the positive γ_1 does not provide a clear explanation for the learning process in response to the country-level information. On the one hand, with the country-level information, individuals could be thoughtful and make sophisticated inferences regarding their own S/E-specific effects. On the other hand, individuals could use country-level information as a shortcut to update their beliefs, which coincidentally leads to updates in the right direction. In addition, I find that γ_1 is generally smaller than γ_2, indicating that individuals update more in response to S/E-specific information compared to country-level information. The magnitude of $\gamma_1 + \gamma_2 + \gamma_3$ is, on average, smaller than the sum of γ_1 and γ_2, suggesting that people update their beliefs less when presented with both pieces of information, compared to the combined effect of receiving them separately. Although these findings offer important insights into how individuals value different signals, they do not address whether individuals can discern the value of various signals, especially when they are presented together, and make inferences based on a higher-quality signal. I will return to these puzzles at the end of this section.

4.1 The Effect of Prior Uncertainty on Beliefs

So far, I have shown that beliefs about the economic consequences of the trade shock are updated in accordance with Bayesian learning, which is consistent across information types and treatment arms. I have also discussed the role of the variance of information, $Variance(Information)$, in belief updating in the Bayesian framework. Another component that I aim to explore is the role of the variance of the prior belief ($Variance(Prior)$), which measures the certainty of individuals about their prior beliefs, in belief updating. I reorganize Equation 1:

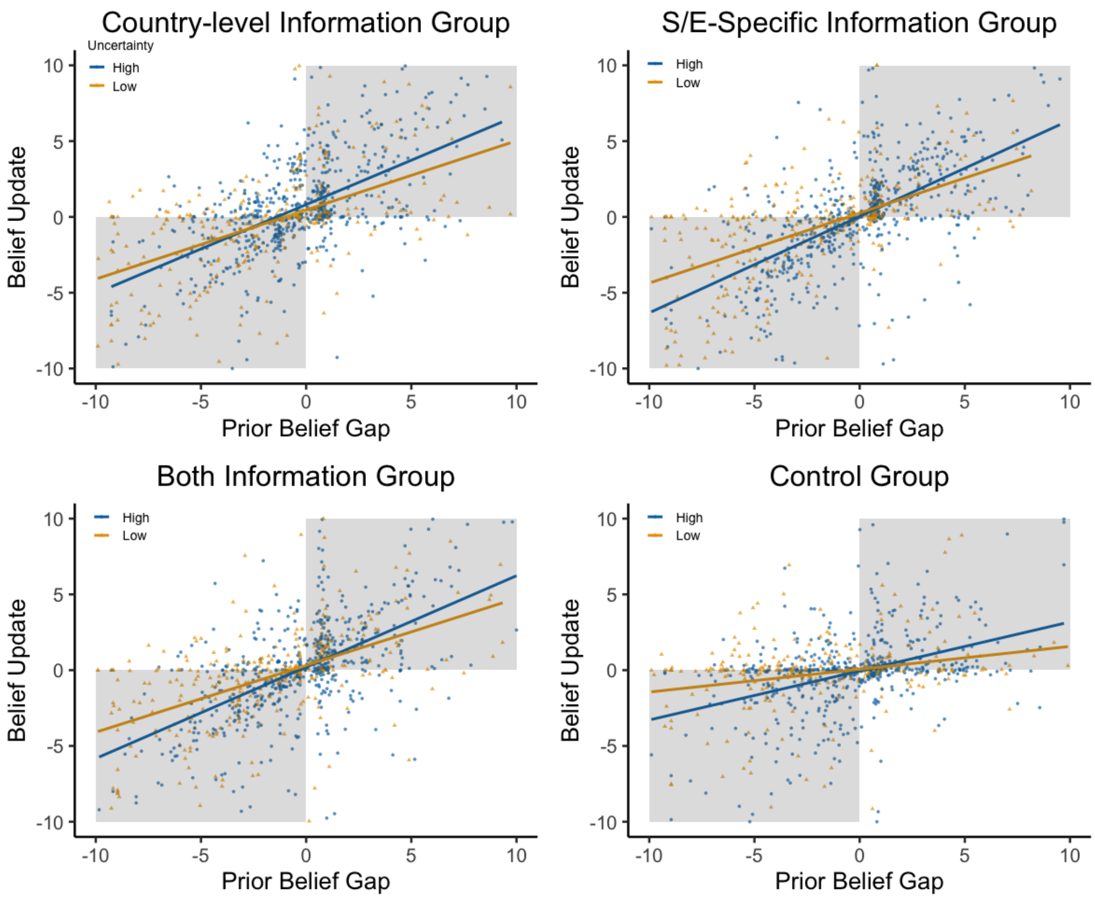
$$\begin{aligned} Posterior - Prior = &(\frac{1}{1 + \frac{Variance(information)}{Variance(Prior)}}) \times Information \\ &- (\frac{1}{1 + \frac{Variance(information)}{Variance(Prior)}}) \times Prior \end{aligned} \tag{3}$$

According to Equation 3, the average beliefs in response to new information should depend on $\frac{Variance(Prior)}{Variance(Information)}$, a ratio of the variance of prior beliefs to the variance of the information.[23] Consequently, another updating pattern compatible with the Bayes' rule is that respondents with greater uncertainty over their prior beliefs update them more in light of the new information, holding the variance of the information constant.

As previously noted, immediately after participants report their prior beliefs in Stage 2, I present them with a 5-point Likert scale asking how confident they are in their answer. The scale ranges from "not at all confident" to "very confident." I operationalize responses by creating a binary measure of uncertainty: $Uncertain_i$, where 1 indicates a high level of uncertainty in the prior belief. The blue dots in Figure 3 represent those with high uncertainty, while their counterparts, those with a low level of prior uncertainty, are indicated by the yellow triangles. The updating behavior of these two groups is presented by the fitted lines on the points. Across all information treatment groups, the blue lines are steeper than the yellow lines, suggesting that highly uncertain participants are more sensitive to new information.

Figure 3 graphically demonstrates a general pattern that individuals with high levels of uncertainty update more in response to the provided information. To test the hypothesis

[23] In their framework, Armantier et al. (2016) assume the Beta distribution and reach the same conclusion as this study.



Note: Similar to Figure 2, this figure shows scatter plots of the prior belief gap (x-axis) and the belief update (y-axis). The blue dots represent individuals with high uncertainty in their prior beliefs, and the yellow triangles represent those with low uncertainty.

Figure 3: Effects of Uncertainty on Beliefs

empirically, I adopt the methodology of Armantier et al. (2016) by fully interacting Equation 2 with $Uncertain_i$:

$$
\begin{aligned}
\Delta\pi_i =& \alpha + \alpha_U Uncertain_i + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3 (T_i^{Country} \times T_i^{S/E}) + \gamma_1 (T_i^{Country} \times \Delta\omega_i) \\
&+ \gamma_2 (T_i^{S/E} \times \Delta\omega_i) + \gamma_3 (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \beta_{U1} (T_i^{Country} \times Uncertain_i) \\
&+ \beta_{U2} (T_i^{S/E} \times Uncertain_i) + \beta_{U3} (T_i^{Country} \times T_i^{S/E} \times Uncertain_i) \\
&+ \gamma_{U1} (T_i^{Country} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U2} (T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) \\
&+ \gamma_{U3} (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \epsilon_i
\end{aligned}
\tag{4}
$$

γ_Us are coefficients for the triple or quadruple interactions among the belief gap, information treatments, and uncertainty over the prior belief. These coefficients measure the difference in average updating in response to the information between individuals with a high and low level of uncertainty over their prior beliefs, controlling for the belief gap. γs + γ_Us thus reflect the belief updates in response to information for those with a high level of uncertainty about their prior beliefs, as opposed to γs, which represent those with a low level of uncertainty.

Panel B in Table 2 on page 20 reports the OLS regression results for Equation 4. The full sample results are shown in column 10. A one percentage point increase in the belief gap, on average, led highly uncertain respondents to update their beliefs 0.05, 0.17, and 0.15 percentage points more than low uncertain respondents in the Country-level, S/E-specific, and Both information groups, respectively. In other words, compared to individuals with low uncertainty, individuals with high uncertainty revise their prior beliefs 8%, 25%, or 25% more. This finding is consistent with Bayes' rule, which states that people with greater uncertainty over their prior beliefs revise them more when presented with new information.

In addition, I find that individuals with high levels of uncertainty over their prior beliefs are, on average, more responsive to the S/E-specific information than the country-level information. It is worthwhile to decipher the result into two parts and explain the rationale separately. Firstly, S/E-specific information is perceived as a more precise signal that individuals can more clearly relate to their prior S/E-specific beliefs. This information serves as a more accurate signal regarding the prior and, as a result, has a smaller variance than country-level information in accordance with Bayesian paradigm. According to Equation 3, information with lower variance is given more weight by respondents when updating their beliefs. Consequently, respondents are more receptive to this S/E-specific information.

Secondly, the effect of precise information on belief updating is amplified by respondents' uncertainty over their prior beliefs. According to Equation 3, subjects' responsiveness to information increases as the variance of their prior beliefs and the variance of the information increase. Building on the first point, I argue that respondents with high uncertainty over their prior beliefs are more receptive to precise information. Panel B of Table 2 shows that, on average, γ_{U2} is positive and statistically significant across treatment arms. This provides consistent evidence for the argument that high uncertainty individuals revise their beliefs more than their low uncertainty counterparts in response to S/E-specific information and in terms of the belief gap.[24]

On the contrary, the updating behavior of respondents with high levels of uncertainty over their priors in response to country-level information is ambiguous, according to both the Bayesian paradigm and the empirical evidence in Table 2. As previously argued, respondents with high uncertainty place greater importance on the provided information, leading to increased responsiveness compared to those with low uncertainty. The country-level information is considered less precise because it is unclear how it relates to the belief about the S/E-specific effect. It is the information that has a larger variance. Based on Equation 3, when updating, individuals assign less importance to information with a larger variance. As a result of these two countervailing forces, it is difficult to predict how high uncertainty

[24]This result holds for almost all treatment arms, except for the employment arm, where γ_{U2} is statistically insignificant but in the right direction.

respondents would respond to the country-level information. This is indicated by Panel B of Table 2, where none of the γ_{U1}s are statistically significant. Nevertheless, given that the majority of the γ_{U1}s are positive, it is a general indication that the effect of uncertainty over prior beliefs has a slightly larger impact on belief updating.

According to Table 2, the updating behavior of high uncertainty respondents who receive both S/E-specific information and country-level information is more similar to that of those who receive only S/E-specific information. Incorporating empirical results of γ_{U1}s, γ_{U2}s, and $\gamma_{U1} + \gamma_{U2} + \gamma_{U3}$s, I find consistent evidence that individuals with high levels of uncertainty over their prior beliefs are, on average, more receptive to new information.

Up to this point, I show that individuals' belief updating behavior in response to new information about the economic consequences is rational and consistent with Bayesian updating. I find that: (1) individuals with larger belief gaps update their beliefs more in response to new information, (2) individuals with higher levels of uncertainty about their prior beliefs are more responsive to new information, and (3) individuals are more responsive to precise information.

4.2 The Effect of Opposing Information on Beliefs

In this subsection, I address questions regarding (1) how people employ country-level information to infer sector/education-specific (S/E-specific) beliefs and (2) whether people weigh S/E-specific information and country-level information differently.

Previously, I have shown that respondents rationally update their S/E-specific beliefs in response to the country-level information, consistent with Bayes' rule. However, the underlying reasons or mechanisms for this update have not been fully explained. On the one hand, it is possible that individuals use the country-level information to make sophisticated inferences about their own S/E-specific effects. On the other hand, they could use country-level information as a shortcut, updating their beliefs accordingly, with the update happens to be in the right direction.

To address this concern, I conduct the following analysis:

$$
\begin{aligned}
\Delta\pi_i =& \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3 (T_i^{Country} \times T_i^{S/E}) + \gamma_1 (T_i^{Country} \times \Delta\omega_i) + \gamma_2 (T_i^{S/E} \times \Delta\omega_i) \\
&+ \gamma_3 (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \gamma_4 (T_i^{Country} \times \Omega_i) + \gamma_5 (T_i^{Country} \times T_i^{S/E} \times \Omega_i) + \epsilon_i
\end{aligned} \tag{5}
$$

where

$$
\Omega_i = \begin{cases} 1, & \text{if } \Delta\omega_i^{Country} \geq 0 \;\&\; \Delta\omega_i \leq 0 \\ -1, & \text{if } \Delta\omega_i^{Country} \leq 0 \;\&\; \Delta\omega_i \geq 0 \\ 0, & \text{otherwise} \end{cases}
$$

and

$$
\Delta\omega_i^{Country} = \omega^*_{Country} - \pi_{i,1}^{S/E}
$$

The variable $\omega^*_{Country}$ represents the best available estimates of the country-level consequences of the import shock, corresponding to the point estimate observed for respondents in both the Country-level Treatment Group and the Both Treatment Group. $\Delta\omega_i^{Country}$ measures the difference between the country-level effects ($\omega^*_{Country}$) and the prior S/E-specific beliefs of respondent i ($\pi_{i,1}^{S/E}$). The difference between the S/E-specific effects and the prior S/E-specific beliefs of respondent i is denoted by $\Delta\omega_i$, where $\Delta\omega_i = \omega_i^{S/E} - \pi_{i,1}^{S/E}$. Ω_i is an indicator variable that captures the discrepancy between the direction of the difference between the country-level effects and the S/E-specific effects, relative to respondent i's prior S/E-specific beliefs. It takes the value 1 (-1) if the difference between the country-level effects and respondent i's prior S/E-specific beliefs is positive (negative), and the difference between the S/E-specific effects and the prior beliefs is negative (positive). I call the scenario "opposing information" when there is a discrepancy between the direction of the difference. Ω_i equals 0 if the two distances do not conflict.

γ_4 in Equation 5 captures whether respondents with opposing information in the Country-

Table 3: The Effect of Opposing Information on Beliefs

	(1) Ctry-level Info (γ_1)	(2) S/E-specific Info (γ_2)	(3) Both Info ($\gamma_1 + \gamma_2 + \gamma_3$)	(4) Opp. Info × Ctry-level Info γ_4	(5) Opp. Info × Both Info $\gamma_4 + \gamma_5$
Belief Update	0.66	0.67	0.60	0.74	-0.08
($\Delta\pi_i$)	[0.61, 0.71]	[0.62, 0.71]	[0.55, 0.65]	[0.29, 1.18]	[-0.54, 0.39]
N	4001				
Adjusted R^2	0.33				

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. The equation for this model is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \gamma_4(T_i^{Country} \times \Omega_i) + \gamma_5(T_i^{Country} \times T_i^{S/E} \times \Omega_i) + \epsilon_i$. See Appendix B.4.2 for the full regression outputs.

level Treatment Group are more likely to update their beliefs in the direction of the presented country-level information or to make inferences about their S/E-specific beliefs.[25] The regression results are presented in Table 3. The positive and statistically significant γ_4 indicates that people in the Country-level Information Group revise their S/E-specific beliefs in the direction of the country-level information. This implies that individuals rely on country-level information as a shortcut to revise their S/E-specific beliefs, rather than using the information for more complex inferences.

This finding raises the question of whether individuals can distinguish the value of different signals and make inferences based on a higher quality signal. As mentioned in the previous section, subjects in the treatment groups could receive one or both types of information: S/E-specific information and country-level information. In the early part of this section, I find that respondents revise their beliefs more when they receive only S/E-specific information than when they receive only country-level information. However, this finding does not disentangle how individuals weigh two types of signals when both types of information are available.

I take advantage of the Both Information Treatment Groups, in which participants receive both S/E-specific information and country-level information, to produce evidence. In Equation 5, $\gamma_4 + \gamma_5$ represents how respondents in the Both Information Group weigh op-

[25] Respondents in the Country-level Information Group observed $\omega^*_{Country}$, but not $\Delta\omega_i$.

posing information, where $\omega^*_{Country}$ and $\Delta\omega_i$ have different signs, when updating their S/E-specific beliefs. According to Table 3, the negative but statistically insignificant $\gamma_4 + \gamma_5$ suggests that respondents essentially treat country-level information and S/E-specific information in a very similar manner. When faced with country-level information, respondents update their beliefs accordingly, and similarly, they update their beliefs in the direction of the S/E-specific information when presented with it. This raises the question of whether individuals can distinguish between different signals based on their quality. Nevertheless, the negative magnitude of $\gamma_4 + \gamma_5$ implies that individuals place a modest value on the S/E-specific information, offering some evidence that people incorporate more precise and specific information.

5. The Effect of Beliefs on Policy Choices

Thus far, I have shown that individuals rationally update their beliefs in response to new information about the economic consequences of the import shock, consistent with Bayesian updating. The remaining question is how changes in beliefs, resulting from the provided information, influence individuals' trade policy choices.

Since beliefs are not randomly assigned and are likely endogenous to the model, I exploit randomly assigned information treatments as instruments to analyze the relationship between beliefs and trade policy choices. To account for any potential unobserved individual heterogeneity, I use the first-differencing method, assuming $t = \{1, 2\}$, which refers to before and after participants receive the treatment. The first- and second-stage equations in the instrumental variables framework are as follows, respectively:

$$\Delta\pi_i = \beta_{1,1}\Delta T_i^{Country} + \beta_{2,1}\Delta T_i^{S/E} + \beta_{3,1}(\Delta T_i^{Country} \times \Delta T_i^{S/E}) + \Delta u_{1,i} \tag{6}$$

$$\Delta P_i = \theta\Delta\pi_i + \Delta u_{2,i} \tag{7}$$

where $\Delta\pi_i = \pi_{i,2}^{S/E} - \pi_{i,1}^{S/E}$, $\Delta T_i = T_{i,2} - T_{i,1}$, and $\Delta P_i = P_{i,2} - P_{i,1}$. $\Delta\pi_i$ is the belief update, which is the difference between subjects' posterior and prior beliefs about their sector/education-specific effects. Since $T_{i,1}s = 0$ for all i, indicating that no one receives information before the treatment, $\Delta T_i s$ is equal to $T_{i,2}$s. This is identical to T_is in Equation 2 and captures whether respondents are assigned to a certain information treatment group. $P_{i,1}$ and $P_{i,2}$ are indicator variables that equal 1 if respondents choose the policy to keep imports from China at the current level in Stage 1 and Stage 5, respectively. Conversely, $P_{i,1}$ and $P_{i,2}$ equal 0 if they select the policy aiming to reduce imports from China by 30%. ΔP_i captures the changes in trade policy choices.

The first-stage examines the relationship between information and beliefs. It is very similar to Equation 2, except that terms fully interacting with the *prior belief gap* ($\Delta\omega_i$) are omitted, since the *prior belief gap* is not randomly assigned. The coefficient of interest, θ, is in the second-stage, which estimates the effect of beliefs on trade policy choices. The first column of Table 4 is the two-stage least squares (2SLS) estimate of θ. The negative and statistically significant relationship suggests that a 1% increase in individuals' beliefs about the sector/education-specific consequences of reducing imports would lead to a 0.16% decrease in their support for a freer trade policy. It suggests that if individuals believe that a more restrictive trade policy will have a positive impact on their sector, especially for people with the same level of education, their support for a freer trade policy would decline.

Several assumptions must hold for the 2SLS estimate to be unbiased. First, due to the experimental setting, the assumption of randomly assigned instruments is satisfied. Second, the exclusion restriction assumption, namely, that the information treatments should only influence trade policy choices through beliefs, is satisfied. While this assumption cannot be tested empirically in a single instrumental variable setting, it can be tested when the model is overidentified: when there are more instruments than endogenous regressors, using overidentifying restrictions (Wooldridge, 2015).[26] Since there are three instruments ($\Delta T_i^{Country}$, $\Delta T_i^{S/E}$,

[26] With one endogenous regressor and three instruments for the regressor, there are $3-1 = 2$ overidentifying

and $\Delta T_i^{Country} \times \Delta T_{i,t}^{S/E}$) and one endogenous regressor ($\Delta \pi_i$), the Sargan-Hansen test can be used to check for overidentifying restrictions. The Hansen J-statistic suggests that the joint null hypothesis that "instruments have no effect on outcomes other than through the first-stage channel" cannot be rejected (Angrist and Pischke, 2009). The result provides some evidence that information influences trade policy choices only through beliefs, consistent with the rational choice framework.

Finally, the third assumption is that information correlates with beliefs. The information is weakly correlated with beliefs, as shown in column 1 of Table 4, where the F-statistic of the weak identification test falls below the rule-of-thumb threshold of statistical significance. With weak instruments, the 2SLS estimate is biased toward the OLS estimate (Angrist and Pischke, 2009). Since the OLS estimate is negative, statistically significant, and of much smaller magnitude according to Column 4 of Table 4, the 2SLS estimate underestimates the effect of belief on policy choices.

The larger and statistically significant effects from the limited information maximum likelihood (LIML) and jackknife instrumental variable approaches confirm that the 2SLS methodology underestimates the impact of information on policy choices. According to column 2 of Table 4, the LIML estimate is -0.19, which represents the "medium-unbiased" estimate for overidentified models (Angrist and Pischke, 2009). Similarly, the jackknife instrumental variable approach yields an estimate of -0.21 for the effect of beliefs on policy choices, which is robust to weak instruments according to Angrist, Imbens and Krueger (1999) and Poi (2006). I conclude that beliefs have a significant effect on policy choices.

In Panel B of Table 4, I present multiple confidence sets that are robust to weak instruments, where the probability of containing the true parameter is tightly controlled (Andrews, Stock and Sun, 2019; Finlay and Magnusson, 2009; Mikusheva and Poi, 2006; Sun, 2018).[27]

restrictions.

[27]When instruments are weak, the approximation of the parameter for the endogenous regressor may not follow a normal distribution. As a result, the confidence interval and hypothesis testing based on the standard t-statistic is unreliable. This leads to a situation where the true probability of committing a Type

Table 4: Effect of Beliefs on Trade Policy Choices

A: The Effect of Beliefs on Trade Policy Choices					
	Change in Policy Choice (ΔP_i)				Policy Choice ($P_{i,t}$)
	(1)	(2)	(3)	(4)	(5)
	2SLS	LIML	Jackknife	OLS	CRE
Belief Update	-0.16	-0.19	-0.21	-0.01	
($\Delta\pi_i$)	[-0.26, -0.06]	[-0.33, -0.06]	[-0.36, -0.06]	[-0.02, -0.01]	
Belief					-0.01
(π_i)					[-0.02, -0.01]
China Arm					-0.17
(X_{China_i})					[-0.20, -0.14]
Democrats					0.08
(X_{Dem_i})					[0.05, 0.11]
Republicans					-0.06
(X_{Rep_i})					[-0.09, -0.02]
White					-0.06
(X_{white_i})					[-0.09, -0.03]
Female					-0.05
(X_{Female_i})					[-0.08, -0.03]
Hansen J-stat (P-value)	0.12				
Weak Identification Test (F-statistic)	5.34				
N/t	4001	4001	4001	4001	4001/2
B: Confidence Sets Robust to Weak Instruments					
	(5)	(6)	(7)		
			Two-step Confidence Sets		
	Homoskedasticity	Heteroskedasticity	Heteroskedasticity		
Conditional Likelihood-ratio (CLR)	[-0.45, -0.11]	[-0.53, -0.12]			
Anderson-Rubin (AR)	[-0.49, -0.10]	[-0.57, -0.11]			
Lagrange Multiplier (LM)	[-0.46, -0.11]	[-0.55, -0.12]			
LM-J Overidentification		[-0.59, -0.11]			
Linear Combination (LC)			[-0.57, -0.11]		

Note: Robust standard errors. 95% confidence levels in parentheses. Several tests available to construct confidence sets include the conditional likelihood-ratio (CLR) test (Moreira, 2003), the Anderson-Rubin (AR) test (Anderson and Rubin, 1949), the Lagrange multiplier (LM) test (Kleibergen, 2002, 2007; Moreira, 2001), a combination of the LM and overidentification (J) tests (LM-J), and a two-step approach proposed by Andrews (2018). The two-step approach constructs a confidence set using the linear combination (LC) test, which combines the K (Kleibergen, 2005) and S (Stock and Wright, 2000) statistics (Andrews, 2018).

All the values within the confidence sets are less than 0, indicating that beliefs about the economic consequences have a significant negative impact on trade policy choices. The weak-instrument robust tests used to construct these robust confidence intervals include the conditional likelihood-ratio (CLR) test (Moreira, 2003), the Anderson-Rubin (AR) test (Anderson and Rubin, 1949), the Lagrange multiplier (LM) test (Kleibergen, 2002, 2007; Moreira, 2001), and a combination of the LM and overidentification (J) tests (LM-J). The confidence intervals in Column 6 are also robust to heteroskedastic errors. Furthermore, in Column 7, I include the two-step confidence sets based on the linear combination (LC) test that combined K (Kleibergen, 2005) and S (Stock and Wright, 2000), as suggested by Andrews (2018) as an alternative approach to constructing robust confidence sets. While the AR, CLR, LM, and LM-J tests ensure that the coefficient has the correct size (the probability of committing a Type I error), the two-step confidence sets improve the coverage probability of the confidence interval by combining two weak-instrument robust statistics, without compromising control over the size of the test (Andrews, 2018; Andrews, Stock and Sun, 2019).

In this section, I show that new information affects trade policy choices only through beliefs about its economic consequences, and that these beliefs, in turn, affect individuals' policy choices. Combined with the findings in of the previous section, which show that individuals update their beliefs about the economic effects of trade rationally, we can form a comprehensive understanding of how information shapes people's trade policy choices.

I error differs from the specified significance level, so that the "Wald-type confidence interval" does not contain the true parameter as frequently as intended (Mikusheva and Poi, 2006). The confidence intervals in Panel B of Table 4 are robust to the weak instruments and have the correct probability of containing the true parameter as often as intended.

6. The Effect of Non-Economic Factors

My results show that individuals place a significant value on economic self-interest, as evidenced by their ability to rationally learn the economic consequences of the trade shock and then apply this to their trade policy choices. However, that only tells half of the story. Since a burgeoning body of literature in the field of IPE posits that public preferences for international trade are shaped by non-economic factors, it is worth exploring the role of these factors.[28]

Notably, partisanship, race, and the identity of the trading partner are important predictors of people's trade preferences (Baccini and Weymouth, 2021; Guisinger, 2017; Milner and Judkins, 2004; Mutz, 2021; Norris and Inglehart, 2019), which can be explained by deeply ingrained cultural or psychological predispositions. Some explanations for these differences in trade preferences include partisan differences in perceptions of the economic competence and reliability of incumbent parties, differences in perceived similarity and trustworthiness among different trading partners, and racial differences in perceptions of threat (Baccini and Weymouth, 2021; Mutz, 2021; Norris and Inglehart, 2019). Furthermore, gender also plays an important role in explaining public opinion on trade, with women generally more likely to support trade restrictions (Brutger and Guisinger, 2022; Burgoon, Hiscox et al., 2004; Kuo and Naoi, 2015). Brutger and Guisinger (2022) attribute this to the fact that women are more likely to react to the possibility of trade-related job insecurity than men.

6.1 The Effect of Non-economic Factors on Policy Choices

In this section, I first examine whether these non-economic characteristics have consistent effects in explaining trade policy choices before and after the information treatment. Table 5 presents the summary statistics of the respondents' trade policy choices by partisanship, race, trade partner identity, and gender. In addition, I categorize respondents based on their

[28] Find Kuo and Naoi (2015) for a detailed summary.

numeracy and trade knowledge, as these variables could potentially affect how people process information. Table 5 only includes respondents who received the information treatment because the remainder of this section focuses on individual heterogeneity in belief updates across demographic groups. Moreover, inspired by Armantier et al. (2016), I combine all the information treatments for the sake of simplicity in presentation.

The second and second-to-last rows in Table 5 show the prior and posterior proportions of respondents who selected the pro-trade option: "US trade policies should aim to keep imports from China (or hypothetical country A) at the current level." Employing the two-proportion Z-test, I find that Democrats, non-whites, those assigned to the hypothetical arm, and males are more likely to support pro-trade policies, which is consistent before and after the information treatments. Among these results, the existing literature has demonstrated similar patterns with respect to partisanship, race, and gender (Baccini and Weymouth, 2021; Brutger and Guisinger, 2022; Mutz, 2021). In terms of the trading partner, people are more inclined to hold anti-trade sentiments toward China as a trading partner, even though the instructions describe hypothetical country A as equivalent to China.

I employ the correlated random effects (CRE) approach to further strengthen the evidence of individual heterogeneity in trade policy choices. This method accounts for the observed covariates that are constant over time, which the previous first-differenced model could not adequately capture, and offers the fixed effects estimates of time-varying cross-sectional variables (Wooldridge, 2013).

To examine the correlation between observed attributes and individual trade policy choices, I estimate the following CRE model:

$$P_{i,t} = \eta_t + \theta\pi_{i,t} + \mathbf{X_i}\boldsymbol{\zeta} + c_i + \epsilon_{i,t} \tag{8}$$

$\mathbf{X_i}$ are the independent variables of interest, which are time-invariant observed covariates that include individual characteristics such as partisanship, race, trading partner identity, and gender. $P_{i,t}$ is the dependent variable, reflecting the subjects' trade policy choices, where

Table 5: Individual Heterogeneity Across Groups

		Party		Race		Trade Partners		Gender		Trade Knowledge		Numeracy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	All	Democrat	Republican	White	Non-white	China	Hypothetical	Female	Male	High	Low	High	Low
Number of Observations	2989	1076	908	2288	701	1513	1476	1524	1465	2157	828	1658	1331
% Prior Policy Choice = 1	41%	50%	33%***	39%	49%***	33%	50%***	39%	44%**	37%	53%***	39%	44%***
Prior Belief	1.48	1.59	1.80	1.48	1.48	1.69	1.27***	1.22	1.76***	1.32	1.90***	1.26	1.76***
% $\lvert$Prior Belief$\rvert \geq 5\%$	20%	22%	22%	20%	22%	22%	19%*	17%	24%***	18%	27%***	18%	24%***
Prior Belief Gap	-0.65	-0.79	-0.92	-0.67	-0.58	-0.87	-0.42***	-0.41	-0.89***	-0.58	-0.84	-0.52	-0.81**
Absolute Belief Gap	2.82	2.89	2.92	2.74	3.06***	2.84	2.80	2.65	2.99***	2.63	3.30***	2.50	3.21***
Prior Uncertainty	2.87	2.81	2.81	2.89	2.81	2.87	2.88	3.08	2.65***	2.92	2.75***	2.94	2.79***
Belief Update	0.02	0.18	-0.27***	0.09	-0.20	-0.12	0.17**	0.15	-0.12*	0.10	-0.19*	0.10	-0.08
Absolute Update	2.47	2.56	2.50	2.37	2.81***	2.34	2.61**	2.63	2.31***	2.42	2.59	2.29	2.70***
Posterior Belief	1.50	1.77	1.53*	1.57	1.29*	1.57	1.44	1.37	1.64**	1.42	1.72**	1.36	1.69***
% Posterior Policy Choice = 1	35%	41%	28%***	34%	40%***	28%	42%***	34%	37%***	30%	48%***	30%	42%***
% ΔPolicy Choice	23%	27%	20%***	21%	32%***	18%	29%***	26%	21%*	21%	29%***	21%	27%***
% Trust = 1	67%	77%	60%***	67%	66%	67%	67%	65%	69%*	69%	63%***	69%	65%**

Note: Compare within demographic group (e.g. Democrats vs. Republicans). T-test for equality of means and Z-test for equality of proportions.

Significant at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$P_{i,t} = 1$ if individual i at time t chooses the option to maintain the existing level of imports from China. As previously mentioned, $t = 1, 2$ refers to periods before and after the information treatment. Time effects, denoted by η_t, capture any potential change between these two points in time that is common to all individuals. $\pi_{i,t}$ is the variable that varies across i and t, measuring beliefs about the economic consequences of the trade shock for individual i at time t. c_i indicates the unobserved heterogeneity across individuals and is the random component of the equation.

$\boldsymbol{\zeta}$ are coefficients of interest that capture the correlation between individual attributes and trade policy choices, controlling for economic self-interest beliefs. Column 5 of Table 4 on page 31 summarizes the regression results. The statistically significant results for the non-economic variables provide additional support for the findings that party identification, gender, race, and the identity of the trading partner are relevant to individual trade policy choices. In addition, the coefficient on economic self-interest beliefs remains statistically significant after controlling for non-economic factors. This bolsters the finding that economic self-interest is significant in shaping individual trade policy choices. It is worth noting that θ in Equation 8, which captures the marginal effect of economic self-interest beliefs on trade policy choices in the CRE framework, is equivalent to the results of the OLS regression, as shown in Column 4 of Table 4. Since the OLS estimate of θ underestimates the effect of economic self-interest beliefs on trade policy choices, the estimates in the 2SLS framework (Column 1 of Table 4), in the LIML framework (Column 2 of Table 4), and the jackknife instrumental framework (Column 3 of Table 4) are more unbiased representations of the causal effect of economic self-interest beliefs.

6.2 The Effect of Non-Economic Factors on Beliefs

After illustrating how individual attributes correlate with trade policy choices, I examine their role in the formation of beliefs. As shown in Table 5, those assigned to the China arm, males, those with less knowledge of trade, and those with lower numeracy levels are more likely to believe that the trade shock has larger economic consequences prior to the treatment. These are also groups of people who hold more extreme beliefs regarding the size of the impact, according to Row 4 of Table 4. However, these measures do not imply that certain groups are more likely to hold inaccurate beliefs about the economic consequences.

Regarding the individual heterogeneity in economic misperceptions, I compare the prior belief gaps and the absolute belief gaps across demographic groups. As previously mentioned, prior belief gaps are calculated as the difference between the actual consequences and the respondents' prior beliefs, while absolute belief gaps are the absolute values of these differences. They measure how informed respondents are about the economic consequences of the import shock. Considering the evidence from both measures, I find that individuals who are Republicans, non-white, male, assigned to the China arm, low in numeracy, and less knowledgeable about trade are more likely to hold inaccurate beliefs about the economic consequences of the import shock.

Finally, how do non-economic factors affect information processing? Is there any demographic group that is more susceptible to new information? To begin to address these puzzles, I analyze the absolute belief update presented in Table 5. This number is the absolute value of the difference between prior and posterior beliefs, serving as an indicator of how much participants revised their beliefs. It suggests that participants who in the hypothetical arm, those who are non-white, female, highly numerate, and have more knowledge of trade are more receptive to new information. This provides some initial evidence of individual heterogeneity across demographic groups. Moreover, assessing responsiveness to new information depends on prior beliefs and the distances between them and the true information. Therefore, inspired by Armantier et al. (2016), I conduct the following regression for all subjects i:

$$\Delta\pi_i = \alpha_1 + \alpha_2 C_i + \alpha_3 T_i + \alpha_4 (C_i \times T_i) + \alpha_5 (C_i \times T_i \times \Delta\omega_i) + \alpha_6 \{(1 - C_i) \times T_i \times \Delta\omega_i\} + \epsilon_i \quad (9)$$

where C_i reprents a vector of indicator variables, including the individual's socioeconomic characteristics, such as partisanship, race, gender, numeracy, trade knowledge, as well as information about the identity of the trading partner. $\Delta\pi_i$ is the belief update for the participant i. T_i is an indicator variable that equals 1 if the respondent receives information. $\Delta\omega_i$ refers to the prior belief gap for i.

Table 6 Heterogenous Updating

	Belief Update ($\Delta\pi_i$)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Democrats	Republicans	White	China Arm	Female	High Trade Knowledge	High Numeracy
w/ Charact.	0.62	0.66	0.63	0.60	0.71	0.70	0.70
(α_5)	[0.57, 0.66]	[0.61, 0.71]	[0.60, 0.66]	[0.56, 0.64]	[0.67, 0.75]	[0.66, 0.73]	[0.66, 0.75]
w/o Charact.	0.66	0.63	0.67	0.68	0.58	0.52	0.58
(α_6)	[0.62, 0.69]	[0.60, 0.66]	[0.61, 0.72]	[0.64, 0.72]	[0.54, 0.62]	[0.47, 0.57]	[0.55, 0.62]
N	4001	4001	4001	4001	4001	3996	4001
Adjusted R^2	0.22	0.32	0.32	0.32	0.33	0.33	0.33

Note: Ordinary least squares (OLS) regression. 95% confidence levels in parentheses. See Appendix B.5 for the full regression results. The equation for this model is $\Delta\pi_i = \alpha_1 + \alpha_2 C_i + \alpha_3 T_i + \alpha_4(C_i \times T_i) + \alpha_5(C_i \times T_i \times \Delta\omega_i) + \alpha_6\{(1 - C_i) \times T_i \times \Delta\omega_i\} + \epsilon_i$.

α_5 and α_6 are coefficients of interest, which capture the responsiveness to information for individuals with and without specific characteristics, respectively. Table 6 shows the regression results. Firstly, by observing the direction of the two coefficients, I find that α_5 and α_6 are positive across all individual attributes. This suggests that, despite potential differences in learning rates, respondents from different groups update their beliefs in a logical manner, consistent with Bayesian updating. Secondly, I examine the heterogeneity in information processing by comparing the magnitudes of α_5 between Democrats and Republicans, as well as the magnitudes of α_5 and α_6 for the remaining attributes. The results show that partisanship and racial identity have no effect on how people process information after controlling for the belief gap, despite their role in explaining trade policy choices. In contrast, I find that, compared to their counterparts, women, high numeracy individuals, people with greater trade knowledge, and people assigned to the hypothetical arm are significantly more responsive to new information, after controlling for the prior belief and belief gap. Similar patterns have also been identified in the information literature, where Armantier et al. (2016) find that female participants are more responsive to new information than males, and Fuster et al. (2022) suggest that numeracy plays an important role in information processing.

Interestingly, the underlying rationale for the gender disparity in learning rates cannot be explained by the differences in belief gaps, prior uncertainty over their prediction, or perception of the credibility of the information, since females in the sample tend to have smaller belief gaps, lower uncertainty over the predictions, and perceive the information as less trustworthy.[29][30] The only explanation for the differences in learning rates between genders is that men and women adopt different information-processing rules (Armantier et al., 2016). Moreover, according to Table 5, we can attribute the higher learning rates of respondents with greater trade knowledge to their strong trust in information or to different learning rules. The greater processing of information by highly numerate respondents can be explained by their higher prior uncertainty over prior beliefs, greater trust in information, or divergent learning rules.

7. Discussion

As scholars increasingly explore the origins of public opinion on trade, economic self-interest explanations seem to have taken a back seat. Instead, non-economic factors such as cultural and psychological considerations have come to the fore. This shift is highlighted

[29]The Variance of Information depends on how confident respondents are about the new information Druckman and McGrath (2019). Since I am combining all the treatment groups, I approximate the level of confidence based on the respondents' level of trust in the researchers.

[30]Level of trust is measured by a question after the main experiment in which respondents specify their level of agreement with the statement "In general, I trust the credibility of people referred to as researchers." The answer is a 5-point Likert scale ranging from "strongly agree" to "strongly disagree." The five-point scale is converted into a binary measure of trust, with the neutral response (neither agree nor disagree) included in the smaller group (trust = 0) that maximizes the statistical power. The percentage of women who trust researchers is 64.96%, compared to 68.49% of men.

by Mutz (2021), who refers to this new emphasis as the "second wave of studies on trade opinion." Rather than shifting attention away from the economic self-interest perspective, my study underscores its continued relevance when properly examined. I argue that the disconnect between economic self-interest theories and trade preferences is rooted in people's economic misperceptions, particularly their incorrect beliefs about the economic impacts of trade. Nevertheless, this misperceptions do not arise from a failure to learn from correct information. I demonstrate that people process information about the economic consequences of trade rationally, in line with Bayesian learning. In addition, these updated beliefs significantly affect people's trade policy choices. This supports the notion that individuals value their economic self-interest. While I acknowledge the presence of non-economic factors such as race, party, and the identity of the trading partner in shaping trade preferences, economic self-interest beliefs still play a significant and non-negligible role. I also demonstrate that none of these non-economic factors result in biased information processing that is inconsistent with Bayesian updating.

My study has broad implications not only for the formation of trade opinions, but also for the design of effective information experiments. Firstly, I find that the effect of information on individuals' trade policy choices is channeled solely through its effect on their beliefs. This suggests that to effectively assess the impact of an information treatment, it is crucial to document individuals' related beliefs, both before and after the treatment. This approach not only uncovers if the information changes these beliefs but also how these altered beliefs subsequently shape policy choices. Yet the IPE information experiment literature has not given adequate attention to measuring beliefs, often analyzing the influence of information on people's opinions as if through a black box.[31] Secondly, I find that people rationally process credible and high-quality information, and they value precise and relevant information

[31] Rho and Tomz (2017) recognize that beliefs play a critical role in connecting information to individual trade policy choices. While they attempt to measure these beliefs, they do so in a separate survey, distinct from their main information experiment.

slightly more than less relevant information. These findings have important implications for formulating messages that resonate in both experimental and real-world contexts. This highlights the necessity for policymakers, communicators, and other relevant groups to ensure the accuracy of information from reliable sources and to tailor it to their target audience to maximize its impact on a broader audience.

Thirdly, my study highlights the central role of economic self-interest in shaping people's trade opinions. It also recognizes the importance of non-economic factors and their effects on the rate at which individuals learn and understand economic self-interest information. This finding suggests that these two origins of trade preferences are not mutually exclusive. Thus, there is a need for a more comprehensive understanding of trade opinion formation, one that takes into account both economic and non-economic factors that affect people's views on trade. Finally, I find that public opinion toward international trade is more malleable in response to new information. While different groups of individuals may process information at varying rates, they all update their beliefs in response to the information, which represents the best available estimates of the economic consequences of trade. This suggests that we can reach a point where there are fewer economic misperceptions about trade, and people form trade preferences that are more aligned with their economic self-interest.

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Learning about Trade
Supplemental Appendix

Hongyi She

A. Additional Details of the Experimental Design

A.1 Policy Choices

The study first randomly assigns respondents to one of the two trading partners: China vs. Hypothetical country A. After being assigned to one of the two trading partners, the experiment moves to the first stage, where they choose their preferred policies with the corresponding trading partner. These account for respondents' baseline trade policy choices. Before stage 1, everyone reads the following script, which is obtained from Rho and Tomz (2017) and Jamal and Milner (2019) with some revisions to fit my contents:

"US businesses and consumers purchase many products that are made in foreign countries. The products from foreign countries are called imports. The share of US imports from low-income countries has increased substantially over time. Some people feel that the US government should limit imports from low-income countries to protect the US economy. Others say that such limits would hurt the US economy."

After the scripts, respondents move to the next screen, where they are asked to make policy choices. Descriptions are slightly different depending on which trading partner they are assigned.

In the China Arm, respondents will see the following screen:

A large percentage of US imports from low-income countries come from China. Manufactured products are the largest component of US imports from China. We would like your *view about the following two trade policies toward China.*

On this issue, which of these policies do you prefer?

US trade policies should aim to keep imports from China at the current level.

US trade policies should aim to reduce imports from China by 30%.

For the hypothetical Arm:

Imagine a hypothetical country A.

A large percentage of US imports from low-income countries come from this imaginary country. Manufactured products are the largest component of US imports from the hypothetical country A. We would like your view about the following two trade policies toward this country.

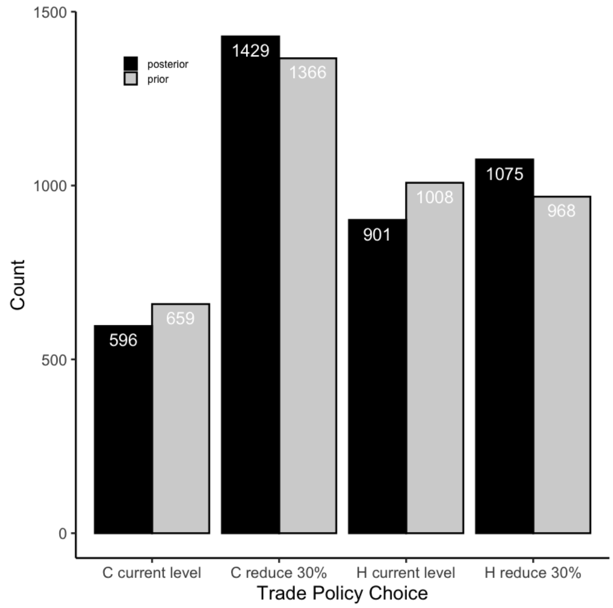
On this issue, which of these policies do you prefer?

US trade policies should aim to keep imports from the hypothetical country A at the current level.

US trade policies should aim to reduce imports from the hypothetical country A by 30%.

Stage 5 is a repetition of stage 1. Respondents are asked to choose between the two policies again. Figure 1 is the detailed summary of trade policy choices respondents made for the whole 4001 sample.

By taking a close look at Figure 1, some patterns show up. Firstly, compared to selecting the policy that aims to keep Chinese imports at the current level, significantly more respondents picked the policy that reduces Chinese imports by 30% prior and posterior compared to the hypothetical arm. Secondly, In the hypothetical arm, the difference between the number of respondents who choose the two policies is much smaller, especially for the prior, compared to the China arm. Last but not least, some respondents change policy choices. And among those who change the policy choice, most of them switch to the more restrictive trade policy: reduce Chinese/hypothetical country A's imports by 30%, as showed in Figure 2 .



Note: C refers to China and H refers to the Hypothetical country.

Figure 1: Posterior And Prior Trade Policy Choices By Trading Partner

A.2 Beliefs

After selecting prior policy choices, the experiment proceeds to the second stage, where respondents are randomly assigned to one of two questions that measure their prior beliefs about the economic consequences of trade with the corresponding trading partner.

The first question asks respondents about employment:

By what percentage do you think the number of employed individuals in your sector (manufacturing/non-manufacturing) who have the same educational background (Bachelor's degree or higher/No bachelor's degree) as you would change if there is a 30% reduction in US imports from China/the Hypothetical country A?

Information in parentheses is based on respondents' answers at the beginning of the survey, with multiple other demographic questions. There is a slider underneath the question that ranges from -10% to 10%. Respondents are instructed to *"move the slider to the percentage that is your best guess."*

The second one is about weekly wages:

By what percentage do you think weekly wages in your sector (Manufacturing/Non-

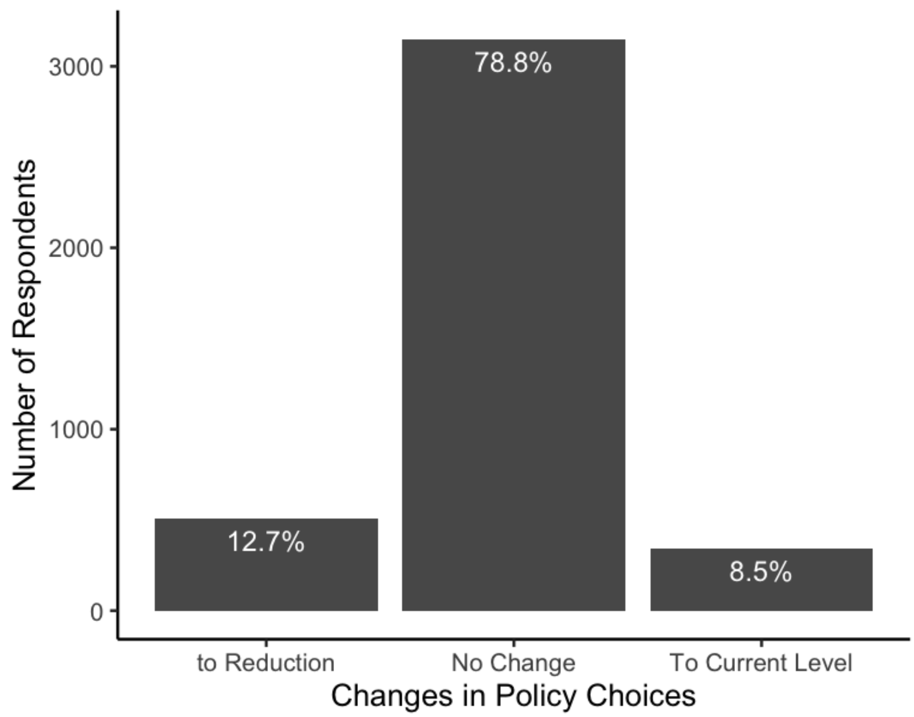


Figure 2: Changes in Trade Policy Choices

manufacturing) who have the same educational background (Bachelor's degree or higher/No bachelor's degree) as you would change if there is a 30% reduction in US imports from China/the Hypothetical country A?

Stage 4 is a repetition of stage 2. Respondents are asked to elicit again their expectations of the economic consequences, which are their posterior beliefs. Figure 2 presents the histogram of the prior and posterior beliefs.

The left panel is the histogram of prior beliefs, the blue dash line is the mean: 1.479%, whereas the median is 0.570%. The predictions are widely dispersed, with a standard deviation of 3.694%. The figure on the right is the histogram of posterior beliefs. The mean is 1.456%, the median is 1.040%, and the standard deviation is 3.304, with less dispersion than prior.

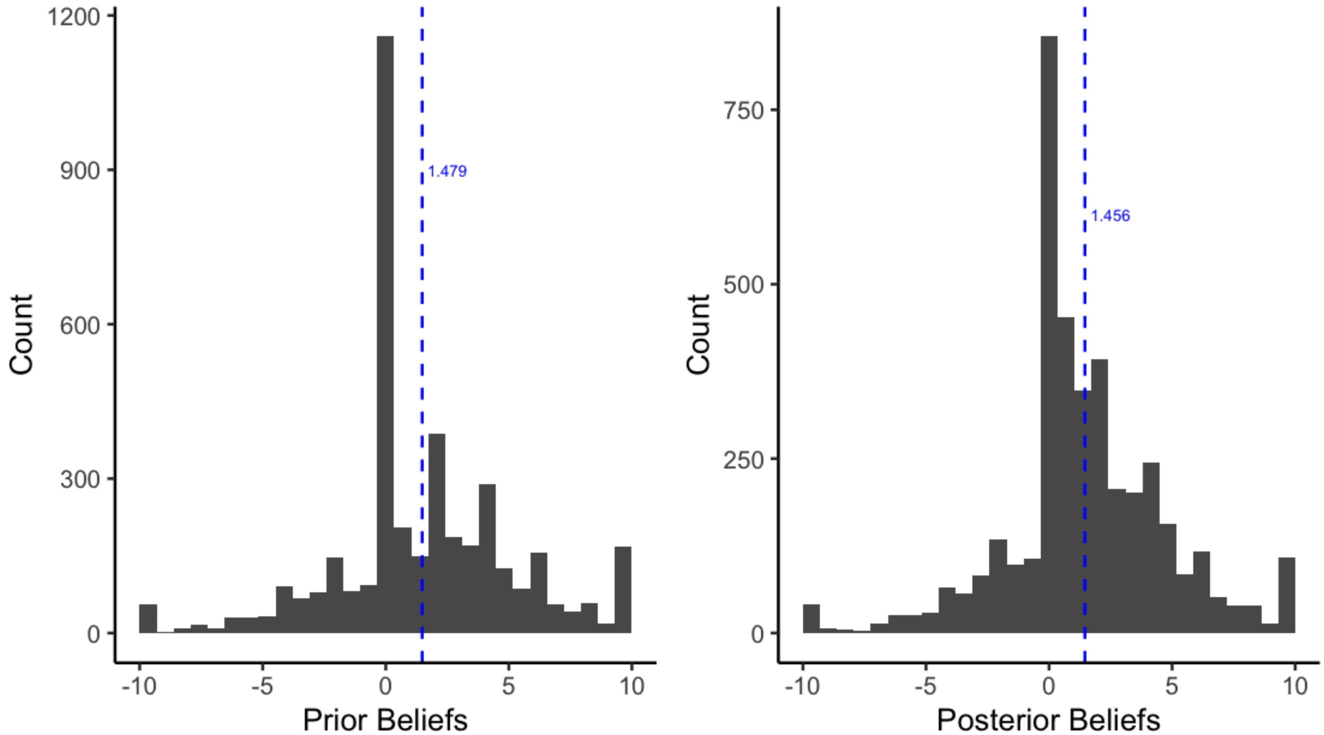


Figure 3: Posterior And Prior Beliefs

A.3 Uncertainty

After eliciting their prior predictions, I ask respondents how confident they are about their predictions. The answer ranges from “Not at all confidence”, “Only slightly confident”, “Somewhat confident”, “Moderately confident”, to “Very confident”.

Figure 3 presents the distribution of respondents’ prior uncertainty over their predictions. 32.1% of respondents say they are somewhat confident about their prediction, which accounts for the largest portion. In general, respondents are pretty confident in their prior beliefs, as more of them choose “Very confident” and “Moderately Confident” than selecting “Only slightly confident” and “Not at all confident”.

I operationalize a binary measure of uncertainty. Figure 3 shows the median answer is “Somewhat confident”. To maximize the statistical power, this answer, along with “Only slightly confident” and “Not at all confident”, are considered high uncertainty, and the rest

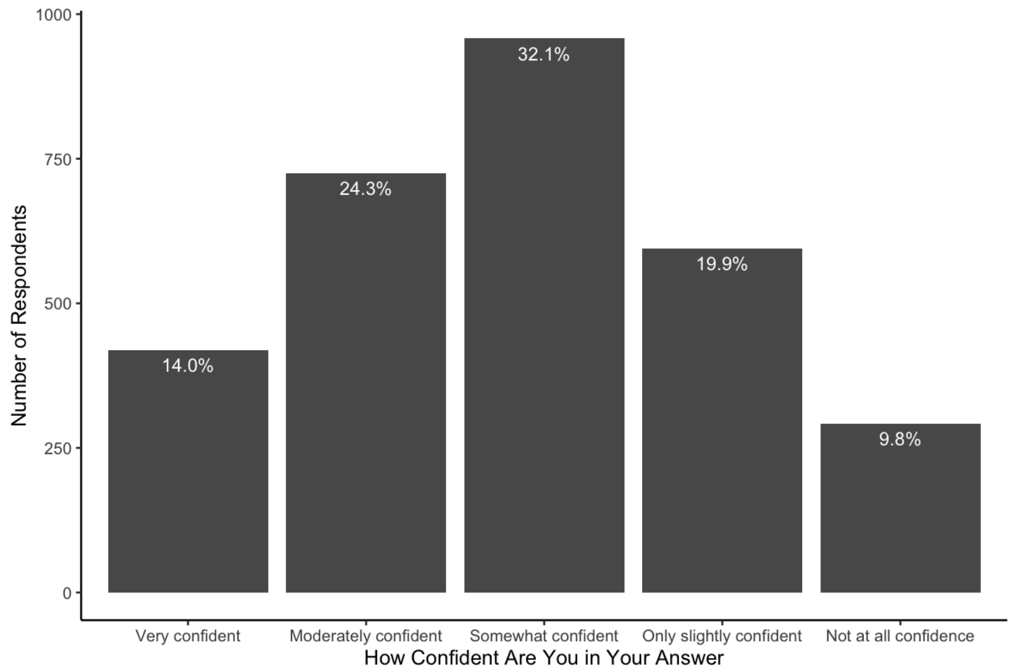


Figure 4: The Distribution of Prior Uncertainty

of the answers are low uncertainty.

A.4 Information

A.4.1 Sector/education-specific Information

Respondents in the **China-employment arm** who are employed in the **manufacturing sector** and **have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-manufacturing sector.

You also indicated earlier that your level of education is Bachelor's degree or higher.

Researchers estimate that a 30% reduction in US imports from China would ***increase the number of employed individuals in your sector (Manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 3.99%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in the number of employed individuals in***

your sector who have the same educational background as you will be between 2.05% and 5.93%.

Respondents in the **China-employment arm** who are employed in the **manufacturing sector** and **do not have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Manufacturing sector.

You also indicated earlier that your level of education is No bachelor's degree.

Researchers estimate that a 30% reduction in US imports from China would ***increase the number of employed individuals in your sector (Manufacturing) who have the same educational background (No bachelor's degree) as you by 4.49%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in the number of employed individuals in your sector who have the same educational background as you will be between 2.45% and 6.54%.***

Respondents in the **China-employment arm** who are employed in the **non-manufacturing sector** and **have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-manufacturing sector.

You also indicated earlier that your level of education is Bachelor's degree or higher.

Researchers estimate that a 30% reduction in US imports from China would ***reduce the number of employed individuals in your sector (Non-manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 0.29%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual change in the number of employed individuals in your sector who have the same educational background as you***

will be between -1.26% and 0.68%.

Respondents in the **China-employment arm** who are employed in the **non-manufacturing sector** and **do not have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-manufacturing sector.

You also indicated earlier that your level of education is No bachelor's degree.

Researchers estimate that a 30% reduction in US imports from China would ***increase the number of employed individuals in your sector (Non-manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 1.04%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual change in the number of employed individuals in your sector who have the same educational background as you will be between -0.22% and 2.29%.***

Respondents in the **China-wage arm** who are employed in the **manufacturing sector** and **have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-manufacturing sector.

You also indicated earlier that your level of education is Bachelor's degree or higher.

Researchers estimate that a 30% reduction in US imports from China would ***reduce weekly wages in your sector (Manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 0.46%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual change in weekly wages in your sector who have the same educational background as you will be between -1.02% and 0.10%.***

Respondents in the **China-wage arm** who are employed in the **manufacturing sector** and **do not have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Manufacturing sector.

You also indicated earlier that your level of education is No bachelor's degree.

Researchers estimate that a 30% reduction in US imports from China would ***increase weekly wages in your sector (Manufacturing) who have the same educational background (No bachelor's degree) as you by 0.10%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual change in weekly wages in your sector who have the same educational background as you will be between -0.51% and 0.71%.***

Respondents in the **China-wage arm** who are employed in the **non-manufacturing sector** and **have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-manufacturing sector.

You also indicated earlier that your level of education is Bachelor's degree or higher.

Researchers estimate that a 30% reduction in US imports from China would ***increase weekly wages in your sector (Non-manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 0.74%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in weekly wages in your sector who have the same educational background as you will be between 0.25% and 1.23%.***

Respondents in the **China-wage arm** who are employed in the **non-manufacturing sector** and **do not have a bachelor's degree**:

You indicated previously that you are currently (or most recently) employed in the Non-

manufacturing sector.

You also indicated earlier that your level of education is No bachelor's degree.

Researchers estimate that a 30% reduction in US imports from China would ***increase weekly wages in your sector (Non-manufacturing) who have the same educational background (Bachelor's degree or higher) as you by 0.82%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in weekly wages in your sector who have the same educational background as you will be between 0.42% and 1.23%.***

Each pieces of information is identical for the hypothetical country arm, with the exception of "China" being replaced by"the hypothetical country A."

A.4.2 Country-level Information

Respondents in the **employment arm**:

Researchers estimate that a 30% reduction in US imports from China would ***increase the number of employed individuals in the US by 4.92%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in the number of employed individuals in the US will be between 3.07% and 6.78%.***

Respondents in the **wage arm**:

Researchers estimate that a 30% reduction in US imports from China would ***increase weekly wages in the US by 0.76%****. Researchers cannot predict the actual increase with certainty. However, they are* ***very (90%) confident that the actual increase in the number of employed individuals in the US will be between 0.34% and 1.18%.***

A.5 Numeracy And Trade Knowledge Questions

A.5.1 Numeracy Questions

There are 5 questions assess respondents' numeracy, borrowed from Armantier et al. (2016) and Fuster et al. (2018) [1]:

1. In a sale, a shop is selling all items at half price. Before the sale, a sofa costs $300. How much will it cost in the sale?

2. Let's say you have $200 in a savings account. The account earns ten per cent interest per year. Interest accrues at each anniversary of the account. If you never withdraw money or interest payments, how much will you have in the account at the end of two years?

3. If the chance of getting a disease is 10%, how many people out of 1,000 would be expected to get the disease?

4. The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?

5. Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up as an even number?

The numeracy questions are landed between Stage 2 and 3, right before respondents see the information.

A.5.2 Trade Knowledge Questions

Four questions measure respondents' knowledge about trade at the end of the survey, taken from *sparknotes* (SparkNotesEditors, 2005) and *ProProfs Quizzes* (Samson, 2022):

1. Which of the following is a situation in which trade is advantageous?

   A. Two countries produce the same goods for the same costs

   B. Two countries produce different goods for different costs

   C. Two countries are isolated

[1] They claimed that their questions were drawn from Lipkus, Samsa and Rimer (2001).

D. Two countries have the same markets

2. When a country exports more than it imports, what is the value of net exports?

A. Negative

B. Positive

C. Zero

D. Need More Information

3. What is the belief that products should be free to move from country to country without barriers?

A. Free Trade

B. Import

C. Export

D. Emigrate

4. What is it called when the government places taxes on imported goods?

A. Subsidies

B. Taxes

C. Quotas

D. Tariffs

B. Additional Results

B.1 Average Summary Statistics by Treatment Groups

Table 1: Average Prior Belief, Belief Gap and Belief Update Comparing Control with Each Treatment Group

	Full Sample			
	Control	Country-level	S/E Specific	Country-level × S/E Specific
Employment Arm				
Number of Observations	506	500	496	500
% Prior Policy Choice = 1	43%	45%	39%	41%
Prior Belief	1.57	1.42	1.416	1.63
Prior Belief Gap	-0.60	-0.44	-0.37	-0.52
Absolute Belief Gap	3.01	2.88	3.12	2.92
Belief Update (Posterior-Prior)	-0.14	0.77***	-0.55*	-0.08
Absolute Update	1.61	2.62***	2.75***	2.41***
Posterior Belief	1.43	2.19***	0.87**	1.55
% Posterior Policy Choice = 1	43%	31%***	39%	36%**
% ΔPolicy Choice	15%	25%***	20%**	21%**
Wage Arm				
Number of Observations	506	497	502	494
% Prior Policy Choice = 1	43%	38%***	42%	42%
Prior Belief	1.36	1.48	1.52	1.44
Prior Belief Gap	-0.73	-0.87	-0.89	-0.79
Absolute Belief Gap	2.63	2.69	2.73	2.56
Belief Update (Posterior-Prior)	-0.16	-0.05	0.05	-0.04
Absolute Update	1.53	2.37***	2.36***	2.31***
Posterior Belief	1.21 [0.31]	1.43 [0.98]	1.57*	1.40
% Posterior Policy Choice = 1	45%	38%***	37%**	36%**
% ΔPolicy Choice	15%	22%***	25%***	28%***

Note: Compare treatments with control. T-test for equality of means Z-test for equality of proportions. Significant at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Policy Choice = 1 if respondents select the policy to keep imports from China (the hypothetical country A) at the current level.

B.2 Visualization of Figure 2 for the Full Range of Data

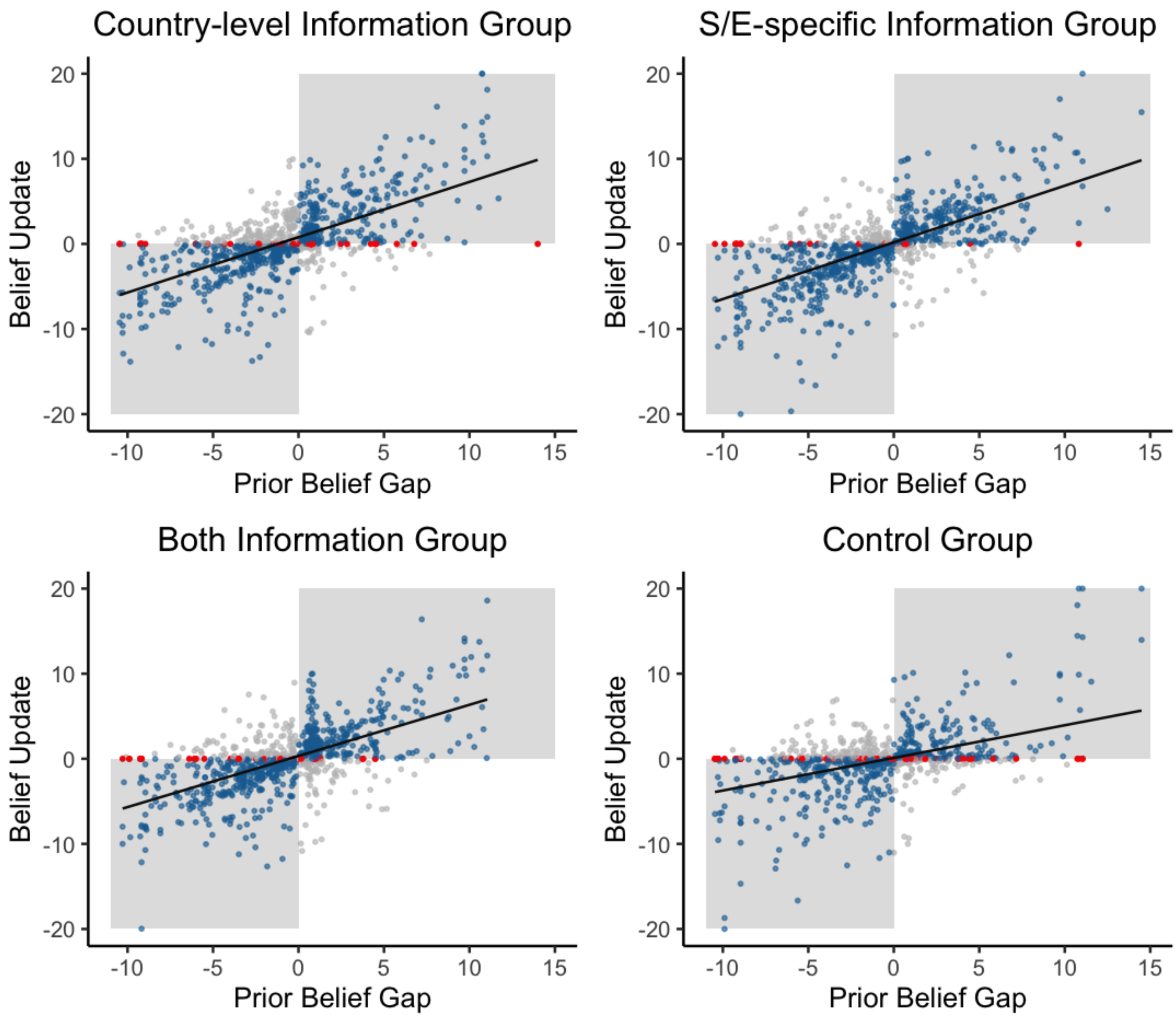


Figure 5: The Effect of Information on Beliefs

B.3 The Effect of Information and Prior Uncertainty on Beliefs by Treatment Groups

Table 2: The Effect of Information on Belief Across Treatment Groups

Coefficient	China Arm			Hypothetical Arm			Full Sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: The Effect of Information on Beliefs									
	Emp	Wage	Emp + Wage	Emp	Wage	Emp + Wage	Emp	Wage	Emp + Wage
Ctry-level Info	0.48	0.80	**0.63**	0.65	0.68	**0.67**	*0.56*	*0.74*	***0.65***
(γ_1)	[0.38, 0.58]	[0.71, 0.90]	[0.56, 0.70]	[0.55, 0.75]	[0.58, 0.79]	[0.60, 0.74]	[0.49, 0.63]	[0.67, 0.81]	[0.60, 0.70]
S/E-specific Info	0.67	0.53	**0.60**	0.82	0.668	**0.74**	*0.74*	*0.60*	***0.67***
(γ_2)	[0.58, 0.76]	[0.44, 0.62]	[0.54, 0.67]	[0.72, 0.92]	[0.56, 0.78]	[0.67, 0.81]	[0.67, 0.80]	[0.53, 0.67]	[0.62, 0.72]
Both Info	0.58	0.55	**0.57**	0.58	0.70	**0.63**	*0.58*	*0.63*	***0.60***
($\gamma_1 + \gamma_2 + \gamma_3$)	[0.49, 0.68]	[0.45, 0.65]	[0.50, 0.64]	[0.48, 0.69]	[0.59, 0.81]	[0.56, 0.70]	[0.51, 0.65]	[0.55, 0.70]	[0.55, 0.65]
B: The Effect of Prior Uncertainty & Information on Beliefs									
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
High - Low:	0.18	-0.13	**0.05**	0.03	0.03	**0.04**	*0.11*	*-0.05*	***0.05***
Ctry-level (γ_{U1})	[-0.02, 0.38]	[-0.32, 0.06]	[-0.09, 0.19]	[-0.18, 0.23]	[-0.17, 0.23]	[-0.10, 0.19]	[-0.03, 0.25]	[-0.19, 0.09]	[-0.05, 0.15]
High - Low:	0.11	0.27	**0.18**	0.02	0.34	**0.16**	*0.08*	*0.28*	***0.17***
S/E-specific (γ_{U2})	[-0.07, 0.29]	[0.08, 0.45]	[0.05, 0.31]	[-0.19, 0.23]	[0.12, 0.56]	[0.01, 0.31]	[-0.06, 0.21]	[0.14, 0.43]	[0.07, 0.27]
High - Low: Both	0.16	0.25	**0.19**	0.01	0.26	**0.12**	*0.08*	*0.24*	***0.15***
($\gamma_{U1} + \gamma_{U2} + \gamma_{U3}$)	[-0.05, 0.37]	[0.05, 0.45]	[0.04, 0.33]	[-0.12, 0.21]	[0.04, 0.48]	[-0.03, 0.27]	[-0.06, 0.22]	[0.09, 0.39]	[0.05, 0.25]
High: Ctry-level	0.58	0.73	**0.66**	0.65	0.72	**0.69**	*0.62*	*0.72*	***0.67***
($\gamma_1 + \gamma_{U1}$)	[0.43, 0.73]	[0.60, 0.87]	[0.56, 0.76]	[0.51, 0.80]	[0.58, 0.86]	[0.59, 0.79]	[0.51, 0.72]	[0.63, 0.82]	[0.60, 0.75]
High: S/E-specific	0.73	0.67	**0.70**	0.84	0.86	**0.82**	*0.78*	*0.75*	***0.76***
($\gamma_2 + \gamma_{U2}$)	[0.61, 0.85]	[0.55, 0.79]	[0.61, 0.79]	[0.70, 0.97]	[0.70, 1.02]	[0.72, 0.93]	[0.69, 0.87]	[0.65, 0.85]	[0.69, 0.82]
High: Both	0.71	0.68	**0.69**	0.59	0.85	**0.69**	*0.63*	*0.76*	***0.69***
($\gamma_{1+2+3} + \gamma_{U1+2+3}$)	[0.54, 0.87]	[0.54, 0.82]	[0.58, 0.80]	[0.45, 0.72]	[0.69, 1.01]	[0.59, 0.79]	[0.53, 0.74]	[0.66, 0.87]	[0.62, 0.76]
N	1021	1004	2025	981	995	1976	2002	1999	4001

Note: Ordinary least squares (OLS) regression. 95% confidence levels in parentheses.

B.3.1 Full Regression Output for Table 2, Panel A

Table 2: The Effect of Information on Beliefs for China-employment arm, China-wage arm, and China arm

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(1)	(2)	(3)
	China-employment Arm	China-wage Arm	China Arm
Ctry-level Info	1.13	0.59	0.84
(β_1)	[0.76, 1.51]	[0.24, 0.95]	[0.58, 1.10]
S/E-specific Info	−0.23	0.36	0.08
(β_2)	[−0.61, 0.14]	[0.01, 0.71]	[−0.18, 0.34]
Both Info	−0.66	−0.65	−0.65
(β_3)	[−1.31, 0.001]	[−1.27, −0.04]	[−1.10, −0.19]
Ctry-level Info × Belief Gap	0.48	0.80	0.63
(γ_1)	[0.38, 0.57]	[0.71, 0.90]	[0.56, 0.70]
S/E-specific Info × Belief Gap	0.67	0.53	0.60
(γ_2)	[0.58, 0.75]	[0.44, 0.62]	[0.54, 0.67]
Both Info × Belief Gap	−0.56	−0.78	−0.67
(γ_3)	[−0.72, −0.40]	[−0.95, −0.62]	[−0.78, −0.55]
Observations	1,021	1,004	2,025
R^2	0.32	0.35	0.32
Adjusted R^2	0.32	0.34	0.32
Residual Std. Error	3.03 [df = 1015]	2.75 [df = 998]	2.92 [df = 2019]
F Statistic	81.02*** [df = 6; 1015]	88.98*** [df = 6; 998]	158.91*** [df = 6; 2019]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. The equation for this model is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \epsilon_i$. This table shows results for the China-employment arm, China-wage arm, and China arm, accordingly.

Table 3: The Effect of Information on Beliefs for hypothetical-employment arm, hypothetical-wage arm, and hypothetical arm

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(4)	(5)	(6)
	Hypothetical-employment Arm	Hypothetical-wage Arm	Hypothetical arm
Ctry-level Info	0.87	0.61	0.73
(β_1)	[0.46, 1.27]	[0.23, 0.99]	[0.45, 1.01]
S/E-specific Info	−0.36	0.81	0.26
(β_2)	[−0.76, 0.05]	[0.42, 1.19]	[−0.02, 0.54]
Both Info	−0.29	−0.85	−0.62
(β_3)	[−0.99, 0.41]	[−1.51, −0.19]	[−1.10, −0.14]
Ctry-level Info × Belief Gap	0.65	0.68	0.67
(γ_1)	[0.55, 0.75]	[0.58, 0.78]	[0.60, 0.74]
S/E-specific Info × Belief Gap	0.82	0.67	0.74
(γ_2)	[0.72, 0.92]	[0.56, 0.78]	[0.67, 0.81]
Both Info × Belief Gap	−0.88	−0.65	−0.78
(γ_3)	[−1.06, −0.71]	[−0.84, −0.47]	[−0.90, −0.65]
Observations	981	995	1,976
R^2	0.36	0.33	0.34
Adjusted R^2	0.36	0.32	0.33
Residual Std. Error	3.21 [df = 975]	3.00 [df = 989]	3.12 [df = 1970]
F Statistic	92.34*** [df = 6; 975]	79.66*** [df = 6; 989]	166.44*** [df = 6; 1970]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. *p<0.1; **p<0.05; ***p<0.01. The equation for this model is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3 (T_i^{Country} \times T_i^{S/E}) + \gamma_1 (T_i^{Country} \times \Delta\omega_i) + \gamma_2 (T_i^{S/E} \times \Delta\omega_i) + \gamma_3 (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \epsilon_i$. This table shows results for the hypothetical-employment arm, hypothetical-wage arm, and hypothetical arm, accordingly.

Table 4: The Effect of Information on Beliefs for employment arm, wage arm, and full sample

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(7)	(8)	(9)
	Employment Arm	Wage Arm	Full Sample
Ctry-level Info	1.02	0.60	0.79
(β_1)	[0.74, 1.29]	[0.34, 0.86]	[0.60, 0.98]
S/E-specific Info	−0.27	0.59	0.18
(β_2)	[−0.55, 0.004]	[0.33, 0.85]	[−0.01, 0.37]
Both Info	−0.52	−0.73	−0.63
(β_3)	[−0.99, −0.04]	[−1.18, −0.28]	[−0.96, −0.30]
Ctry-level Info × Belief Gap	0.56	0.74	0.65
(γ_1)	[0.49, 0.63]	[0.67, 0.81]	[0.60, 0.70]
S/E-specific Info × Belief Gap	0.74	0.59	0.67
(γ_2)	[0.67, 0.80]	[0.52, 0.66]	[0.62, 0.71]
Both Info × Belief Gap	−0.71	−0.71	−0.71
(γ_3)	[−0.83, −0.59]	[−0.83, −0.59]	[−0.80, −0.63]
Observations	2,002	1,999	4,001
R^2	0.34	0.33	0.33
Adjusted R^2	0.34	0.33	0.33
Residual Std. Error	3.12 [df = 1996]	2.88 [df = 1993]	3.02 [df = 3995]
F Statistic	171.57*** [df = 6; 1996]	165.35*** [df = 6; 1993]	324.10*** [df = 6; 3995]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. The equation for this model is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \epsilon_i$. This table shows results for the employment arm, wage arm, and full sample, accordingly.

B.3.1 Full Regression Output for Table 2, Panel B

Table 5: The Effect of Prior Uncertainty & Information on Beliefs for China-employment arm, China-wage arm, and China arm

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(1)	(2)	(3)
	China-employment Arm	China-wage Arm	China Arm
Uncertainty	−0.10	−0.59	−0.36
(α_U)	[−0.58, 0.38]	[−1.01, −0.18]	[−0.68, −0.04]
Ctry-level Info	0.91	0.70	0.74
(β_1)	[0.28, 1.54]	[0.10, 1.29]	[0.30, 1.17]
S/E-specific Info	−0.04	0.56	0.28
(β_2)	[−0.66, 0.58]	[−0.07, 1.20]	[−0.16, 0.73]
Both Info	−0.36	−1.10	−0.64
(β_3)	[−1.43, 0.71]	[−2.19, −0.01]	[−1.41, 0.13]
Ctry-level Info × Belief Gap	0.40	0.87	0.61
(γ_1)	[0.27, 0.53]	[0.74, 0.99]	[0.52, 0.70]
S/E-specific Info × Belief Gap	0.62	0.41	0.52
(γ_2)	[0.48, 0.75]	[0.27, 0.55]	[0.42, 0.62]
Both Info × Belief Gap	−0.47	−0.84	−0.63
(γ_3)	[−0.70, −0.25]	[−1.08, −0.60]	[−0.79, −0.46]
Ctry-level Info × Uncertainty	0.44	0.44	0.52
(β_{U1})	[−0.48, 1.36]	[−0.40, 1.28]	[−0.11, 1.15]
S/E-specific Info × Uncertainty	−0.28	0.15	−0.06
(β_{U2})	[−1.20, 0.64]	[−0.71, 1.02]	[−0.70, 0.57]
Both Info × Uncertainty	−0.62	0.13	−0.34
(β_{U3})	[−2.06, 0.82]	[−1.25, 1.51]	[−1.34, 0.67]
Ctry-level Info × Belief Gap × Uncertainty	0.18	−0.13	0.05
(γ_{U1})	[−0.02, 0.38]	[−0.32, 0.06]	[−0.09, 0.19]
S/E-specific Info × Belief Gap × Uncertainty	0.11	0.27	0.18
(γ_{U2})	[−0.07, 0.29]	[0.08, 0.45]	[0.05, 0.31]
Both Info × Belief Gap × Uncertainty	−0.13	0.12	−0.05
(γ_{U3})	[−0.47, 0.21]	[−0.22, 0.45]	[−0.28, 0.19]
Observations	1,021	1,004	2,025
R^2	0.33	0.37	0.33
Adjusted R^2	0.32	0.36	0.33
Residual Std. Error	3.02 [df = 1008]	2.72 [df = 991]	2.91 [df = 2012]
F Statistic	38.50*** [df = 13; 1008]	44.18*** [df = 13; 991]	76.18*** [df = 13; 2012]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. *p<0.1; **p<0.05; ***p<0.01. The equation for this model is $\Delta\pi_i = \alpha + \alpha_U Uncertain_i + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \beta_{U1}(T_i^{Country} \times Uncertain_i) + \beta_{U2}(T_i^{S/E} \times Uncertain_i) + \beta_{U3}(T_i^{Country} \times T_i^{S/E} \times Uncertain_i) + \gamma_{U1}(T_i^{Country} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U2}(T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U3}(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \epsilon_i$. This table shows results for the China-employment arm, China-wage arm, and China arm, accordingly.

Table 6: The Effect of Prior Uncertainty & Information on Beliefs for hypothetical-employment arm, hypothetical- wage arm, and hypothetical arm

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(4)	(5)	(6)
	Hypothetical-employment Arm	Hypothetical-wage Arm	Hypothetical arm
Uncertainty	−0.04	0.11	0.04
(α_U)	[−0.54, 0.47]	[−0.35, 0.58]	[−0.31, 0.38]
Ctry-level Info	0.58	1.04	0.79
(β_1)	[−0.08, 1.25]	[0.38, 1.70]	[0.32, 1.26]
S/E-specific Info	−0.20	0.90	0.41
(β_2)	[−0.90, 0.50]	[0.27, 1.53]	[−0.06, 0.88]
Both Info	−0.17	−0.89	−0.60
(β_3)	[−1.32, 0.99]	[−2.00, 0.21]	[−1.40, 0.21]
Ctry-level Info × Belief Gap	0.63	0.69	0.65
(γ_1)	[0.48, 0.77]	[0.54, 0.83]	[0.55, 0.75]
S/E-specific Info × Belief Gap	0.81	0.52	0.67
(γ_2)	[0.66, 0.97]	[0.37, 0.67]	[0.55, 0.78]
Both Info × Belief Gap	−0.86	−0.61	−0.74
(γ_3)	[−1.12, −0.60]	[−0.88, −0.35]	[−0.93, −0.56]
Ctry-level Info × Uncertainty	0.48	−0.79	−0.15
(β_{U1})	[−0.50, 1.47]	[−1.72, 0.14]	[−0.83, 0.53]
S/E-specific Info × Uncertainty	−0.22	−0.35	−0.35
(β_{U2})	[−1.23, 0.78]	[−1.26, 0.57]	[−1.04, 0.33]
Both Info × Uncertainty	−0.23	0.20	0.06
(β_{U3})	[−1.77, 1.32]	[−1.26, 1.65]	[−1.00, 1.13]
Ctry-level Info × Belief Gap × Uncertainty	0.03	0.03	0.04
(γ_{U1})	[−0.18, 0.23]	[−0.17, 0.23]	[−0.10, 0.19]
S/E-specific Info × Belief Gap × Uncertainty	0.02	0.34	0.16
(γ_{U2})	[−0.19, 0.23]	[0.12, 0.56]	[0.01, 0.31]
Both Info × Belief Gap × Uncertainty	−0.04	−0.11	−0.08
(γ_{U3})	[−0.40, 0.32]	[−0.48, 0.26]	[−0.34, 0.18]
Observations	981	995	1,976
R^2	0.36	0.34	0.34
Adjusted R^2	0.35	0.33	0.34
Residual Std. Error	3.22 [df = 968]	2.97 [df = 982]	3.12 [df = 1963]
F Statistic	42.50*** [df = 13; 968]	39.48*** [df = 13; 982]	77.88*** [df = 13; 1963]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. *p<0.1; **p<0.05; ***p<0.01. The equation for this model is $\Delta\pi_i = \alpha + \alpha_U Uncertain_i + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3 (T_i^{Country} \times T_i^{S/E}) + \gamma_1 (T_i^{Country} \times \Delta\omega_i) + \gamma_2 (T_i^{S/E} \times \Delta\omega_i) + \gamma_3 (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \beta_{U1} (T_i^{Country} \times Uncertain_i) + \beta_{U2} (T_i^{S/E} \times Uncertain_i) + \beta_{U3} (T_i^{Country} \times T_i^{S/E} \times Uncertain_i) + \gamma_{U1} (T_i^{Country} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U2} (T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U3} (T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \epsilon_i$. This table shows results for the hypothetical-employment arm, hypothetical-wage arm, and hypothetical arm, accordingly.

Table 7: The Effect of Prior Uncertainty & Information on Beliefs for employment arm, wage arm, and full sample

	Dependent variable:		
	Belief Update ($\Delta\pi_i$)		
	(7)	(8)	(9)
	Employment Arm	Wage Arm	Full Sample
Uncertainty	−0.07	−0.25	−0.16
(α_U)	[−0.42, 0.28]	[−0.56, 0.06]	[−0.40, 0.07]
Ctry-level Info	0.74	0.89	0.76
(β_1)	[0.29, 1.20]	[0.45, 1.34]	[0.44, 1.08]
S/E-specific Info	−0.10	0.76	0.36
(β_2)	[−0.56, 0.36]	[0.31, 1.20]	[0.04, 0.68]
Both Info	−0.26	−0.97	−0.60
(β_3)	[−1.04, 0.52]	[−1.74, −0.19]	[−1.15, −0.05]
Ctry-level Info × Belief Gap	0.51	0.78	0.63
(γ_1)	[0.41, 0.60]	[0.68, 0.87]	[0.56, 0.70]
S/E-specific Info × Belief Gap	0.70	0.46	0.59
(γ_2)	[0.60, 0.80]	[0.36, 0.57]	[0.51, 0.66]
Both Info × Belief Gap	−0.65	−0.72	−0.68
(γ_3)	[−0.82, −0.48]	[−0.89, −0.54]	[−0.80, −0.55]
Ctry-level Info × Uncertainty	0.48	−0.19	0.19
(β_{U1})	[−0.19, 1.15]	[−0.82, 0.44]	[−0.27, 0.66]
S/E-specific Info × Uncertainty	−0.25	−0.13	−0.21
(β_{U2})	[−0.93, 0.43]	[−0.76, 0.50]	[−0.68, 0.25]
Both Info × Uncertainty	−0.45	0.16	−0.17
(β_{U3})	[−1.51, 0.60]	[−0.84, 1.16]	[−0.90, 0.56]
Ctry-level Info × Belief Gap × Uncertainty	0.11	−0.05	0.05
(γ_{U1})	[−0.03, 0.25]	[−0.19, 0.09]	[−0.05, 0.15]
S/E-specific Info × Belief Gap × Uncertainty	0.08	0.28	0.17
(γ_{U2})	[−0.06, 0.21]	[0.14, 0.43]	[0.07, 0.27]
Both Info × Belief Gap × Uncertainty	−0.11	0.01	−0.07
(γ_{U3})	[−0.35, 0.13]	[−0.24, 0.25]	[−0.24, 0.11]
Observations	2,002	1,999	4,001
R^2	0.34	0.35	0.33
Adjusted R^2	0.34	0.34	0.33
Residual Std. Error	3.12 [df = 1989]	2.86 [df = 1986]	3.01 [df = 3988]
F Statistic	80.01*** [df = 13; 1989]	80.92*** [df = 13; 1986]	153.27*** [df = 13; 3988]

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. *p<0.1; **p<0.05; ***p<0.01. The equation for this model is $\Delta\pi_i = \alpha + \alpha_U Uncertain_i + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \beta_{U1}(T_i^{Country} \times Uncertain_i) + \beta_{U2}(T_i^{S/E} \times Uncertain_i) + \beta_{U3}(T_i^{Country} \times T_i^{S/E} \times Uncertain_i) + \gamma_{U1}(T_i^{Country} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U2}(T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \gamma_{U3}(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i \times Uncertain_i) + \epsilon_i$. This table shows results for the employment arm, wage arm, and full sample, accordingly.

B.4 The Effect of Opposing Information on Beliefs

B.4.1 Opposing Information

I define a respondent as receiving opposing information if: (1) they are assigned to the Both Information Group, and (2) if $\Delta\omega_i^{Country}$ and $\Delta\omega_i$ are in opposite directions. There is no situation where $\Delta\omega_i^{Country}$ and $\Delta\omega_i$ are both zero.

$$\Omega_i = \begin{cases} 1, & \text{if } \ \Delta\omega_i^{Country} \geq 0 \ \& \ \Delta\omega_i \leq 0 \\ -1, & \text{if } \ \Delta\omega_i^{Country} \leq 0 \ \& \ \Delta\omega_i \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

and

$$\Delta\omega_i^{Country} = \omega^*_{Country} - \pi_{i,1}^{S/E}$$

The following is the distribution of Ω_i:

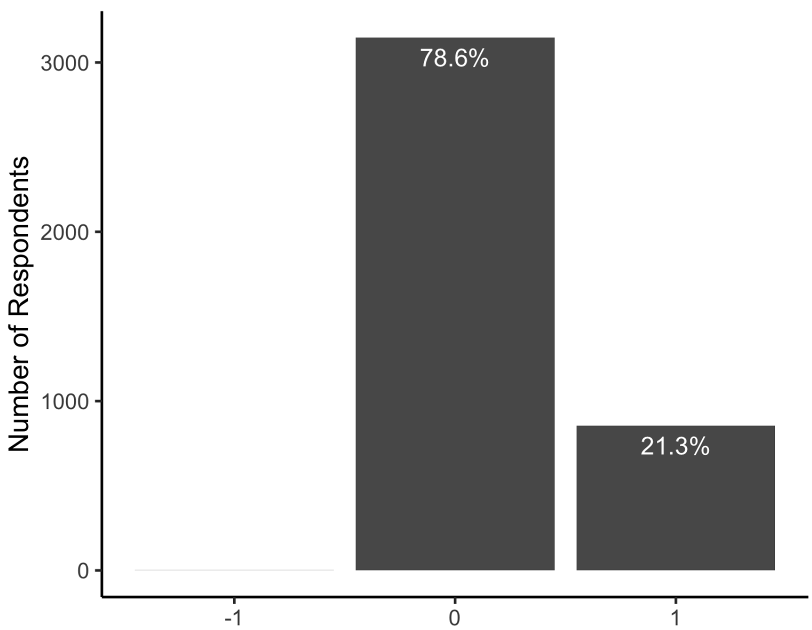


Figure 6: The Distribution of Ω_i

B.4.2 Full Output for Table 3

Table 8: The Effect of Opposing Information on Beliefs

	Dependent variable:
	Belief Update ($\Delta\pi_i$)
Ctry-level Info	0.62
(β_1)	[0.41, 0.84]
S/E-specific Info	0.18
(β_2)	[−0.01, 0.37]
Both Info	−0.45
(β_3)	[−0.81, −0.10]
Ctry-level Info × Belief Gap	0.66
(γ_1)	[0.61, 0.71]
S/E-specific Info × Belief Gap	0.67
(γ_2)	[0.62, 0.71]
Both Info × Belief Gap	−0.73
(γ_3)	[−0.81, −0.64]
Ctry-level Info × Ω_i	0.74
(γ_4)	[0.29, 1.18]
Both Info × Ω_i	−0.81
(γ_5)	[−1.46, −0.17]
Observations	4,001
R^2	0.329
Adjusted R^2	0.328
Residual Std. Error	3.019 (df = 3993)
F Statistic	244.947*** (df = 8; 3993)

Note: Ordinary least squares (OLS) regression. 95% confidence intervals in parentheses. The equation for this table is $\Delta\pi_i = \alpha + \beta_1 T_i^{Country} + \beta_2 T_i^{S/E} + \beta_3(T_i^{Country} \times T_i^{S/E}) + \gamma_1(T_i^{Country} \times \Delta\omega_i) + \gamma_2(T_i^{S/E} \times \Delta\omega_i) + \gamma_3(T_i^{Country} \times T_i^{S/E} \times \Delta\omega_i) + \gamma_4(T_i^{Country} \times \Omega_i) + \gamma_5(T_i^{Country} \times T_i^{S/E} \times \Omega_i) + \epsilon_i$.

B.5 Full Output for Table 6

Table 9: Heterogeneous Updating for Democrats, Republicans, and White Respondents

	Dependent variable:		
	Belief Update (Δpi_i)		
	Democrats	Republicans	White
Treatment	0.30	0.48	0.19
(α_3)	[0.16, 0.44]	[0.35, 0.61]	[−0.04, 0.41]
Charact.	−0.10	−0.51	−0.14
(α_2)	[−0.40, 0.20]	[−0.86, −0.16]	[−0.35, 0.08]
Treatment × Charact.	0.47	0.36	0.46
(α_4)	[0.09, 0.85]	[−0.06, 0.79]	[0.12, 0.80]
Treatment × Charact. × Belief Gap	0.62	0.66	0.63
(α_5)	[0.57, 0.66]	[0.61, 0.71]	[0.60, 0.66]
Treatment × w/o Charact. × Belief Gap	0.66	0.63	0.67
(α_6)	[0.62, 0.69]	[0.60, 0.66]	[0.61, 0.72]
Observations	4,001	4,001	4,001
R^2	0.33	0.33	0.32
Adjusted R^2	0.32	0.32	0.32
Residual Std. Error (df = 3996)	3.03	3.03	3.03
F Statistic (df = 5; 3996)	385.72***	384.80***	384.39***

Note: Ordinary least squares (OLS) regression. 95% confidence levels in parentheses. The equation for this table is $\Delta\pi_i = \alpha_1 + \alpha_2 C_i + \alpha_3 T_i + \alpha_4(C_i \times T_i) + \alpha_5(C_i \times T_i \times \Delta\omega_i) + \alpha_6\{(1 - C_i) \times T_i \times \Delta\omega_i\} + \epsilon_i$.

Table 10: Heterogeneous Updating for China Arm, Female, High Trade Knowledge, and High Numeracy

	Dependent variable:			
	Belief Update (Δpi_i)			
	China Arm	Female	High Trade Knowledge	High Numeracy
Treatment	0.45	0.40	0.25	0.40
(α_3)	[0.30, 0.61]	[0.24, 0.56]	[0.04, 0.46]	[0.23, 0.56]
Charact.	−0.26	−0.05	−0.09	−0.11
(α_2)	[−0.52, 0.01]	[−0.31, 0.20]	[−0.31, 0.13]	[−0.36, 0.14]
Treatment×Charact.	0.21	0.10	0.34	0.18
(α_4)	[−0.14, 0.55]	[−0.24, 0.44]	[0.01, 0.67]	[−0.15, 0.51]
Treatment×Charact.×Belief Gap	0.60	0.71	0.70	0.70
(α_5)	[0.56, 0.64]	[0.67, 0.75]	[0.66, 0.73]	[0.66, 0.75]
Treatment×w/o Charact.×Gap	0.68	0.58	0.52	0.58
(α_6)	[0.64, 0.72]	[0.54, 0.62]	[0.47, 0.57]	[0.55, 0.62]
Observations	4,001	4,001	3,996	4,001
R^2	0.32	0.33	0.33	0.33
Adjusted R^2	0.32	0.33	0.33	0.33
Residual Std. Error	3.03 [df = 3996]	3.02 [df = 3996]	3.02 [df = 3991]	3.03 [df = 3996]
F Statistic	384.44*** [df = 5; 3996]	387.68*** [df = 5; 3996]	389.66*** [df = 5; 3991]	386.63*** [df = 5; 3996]

Note: Ordinary least squares (OLS) regression. 95% confidence levels in parentheses. The equation for this table is $\Delta\pi_i = \alpha_1 + \alpha_2 C_i + \alpha_3 T_i + \alpha_4(C_i \times T_i) + \alpha_5(C_i \times T_i \times \Delta\omega_i) + \alpha_6\{(1 - C_i) \times T_i \times \Delta\omega_i\} + \epsilon_i$.

C. Sociotropic Considerations

To determine whether respondents have sociotropic concerns for their trade preferences, I further analyzed respondents' trade policy choices in the Both Information Group. There is a longstanding academic debate about sociotropic and economic self-interest considerations of policy preferences dating back to Kinder and Kiewiet (1981) (Bechtel and Liesch, 2020; Curtis, Jupille and Leblang, 2014; Fordham and Kleinberg, 2012; Jamal and Milner, 2019; Maria Schaffer and Spilker, 2019; Sears and Funk, 1991). In addition, Mansfield and Mutz (2009) contend that Americans' opinions on trade are influenced by their perception of the overall impact on the US, as opposed to their own personal economic gain.

To contribute to this debate, I conduct a simple regression on respondents in the Both Information Group. I identify all the respondents who receive opposing signals about the economic consequences of the trade shock, that is, they observe positive country-level information and negative S/E-specific information.[2] Comparing the changes in their trade policy choices with counterparts who observe the information in the same direction, I find that they are slightly (but not significantly) more likely to switch to choose the restrictive policy. This provides suggestive evidence that it is difficult to justify the existence of socitropic considerations, especially when people have access to information that is more related to their own well-being.

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